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Investigating the behaviour of individual UK prices, and gauging the implications thereof for monetary policy

A context statement presented to Middlesex University
as part of the requirements for the award of a PhD by Public Works

Colin Ellis

November 2013

Investigating the behaviour of individual UK prices, and gauging the implications thereof for monetary policy

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List of Public Works submitted alongside the context statement

1. Bunn, P, and Ellis, C (2012a), 'How do individual UK producer prices behave?', *The Economic Journal*, Vol. 122 (February), pages F16-F34.
2. Bunn, P, and Ellis, C (2012b), 'Examining the behaviour of individual UK consumer prices', *The Economic Journal*, Vol. 122 (February), pages F35-F55.
3. Ellis, C (2009a), 'Do supermarket prices change from week to week?', *Bank of England Working Paper* No. 378.
4. Ellis, C (2012), 'Measuring UK inflation; Practical differences and issues', *World Economics*, Vol. 13, No. 4, pages 99-112.
5. Ellis, C (2009b), 'Why we should change the inflation target (but not in the way you might think)', *The Business Economist*, Vol. 40, No. 1, pages 21-30.
6. Mumtaz, H, Zabczyk, P, and Ellis, C (2009), 'What lies beneath: what can disaggregated data tell us about the behaviour of prices?', *Bank of England Working Paper* No. 364.

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Acknowledgements

I would very much like to thank all the people that have helped me, directly or otherwise, to prepare this submission. I am incredibly grateful for all the assistance, guidance and advice that I have encountered in various settings.

Particular thanks must go to my co-authors for some of the public works in this submission – Phil Bunn, Pawel Zabczyk and Haroon Mumtaz. Their insight, hard work and contributions were incredibly valuable, and all joint papers were genuine collaborations. I have enjoyed working with many different colleagues during my career, but their specific support and enthusiasm undoubtedly helped sustain my own interest and progress in this field.

I would also like to thank the various other colleagues who offered helpful advice and comments both on the original works as they were produced and published, and subsequently to this context statement. Special thanks are due to Simon Price, who first properly introduced me to the world of academic research and nurtured my interests and skills; and my supervisor Marian Rizov, whose guidance and support with this statement were invaluable.

I would also like to extend particular thanks to the Office for National Statistics and Nielsen for providing access to the data used in the analysis. Thanks are also due to Patricia Babatunde, Richard Barwell, Charlie Bean, Simon Boswell, Alex Bowen, Mark Cornelius, Neal Hatch, Stephen Hilton, Steve Machin, Steve Millard, Nick Oulton, Miles Parker, Brian Sturgess, Garry Young, Mike Watkins, seminar participants from the Bank of England, and anonymous referees for the Bank of England Working Paper series and the *Economic Journal*.

Finally, I would also like to thank my family – Rosie, Faith and Katie – for supporting me during the many years over which this research was conducted and compiled.

Abstract

This context statement and the associated public works examine the behaviour of individual goods and services prices in the United Kingdom, and the implications thereof for monetary policy and monetary policy makers. Until recently, many macroeconomic and monetary policy models have made relatively simplistic assumptions about the microeconomic behaviour of prices. Research has uncovered that, in many countries, these assumptions may not hold. However, there has been almost no prior empirical work that has examined how individual prices actually behave in the United Kingdom.

The research embodied in this context statement and public works represents original work that explores how individual UK prices of goods and services are measured and actually behave at the microeconomic level, using both official and private sector data sources that have not previously been employed in academic research. This analysis uncovers the rich heterogeneity in pricing behaviour that actually exists at the microeconomic level. By examining the varied datasets, it is apparent that the standard assumptions in typical macroeconomic and monetary policy models are frequently violated.

The empirical behaviour of individual prices also has important implications for monetary policy and monetary policy makers. These include the optimal design of monetary policy, in terms of the role of inflation targeting, the correct monetary policy response to the different shocks that hit the economy, and the challenge of capturing the rich heterogeneity that is present in the UK economy within a parsimonious model.

Key words: Monetary Policy, Microeconomic Prices, Heterogeneity, Temporary Price Changes, Central Banks, Inflation Targeting.

Chapter 1 Introduction

After the experiences of the 1970s and 1980s, monetary policy in advanced economies is now focused on controlling inflation. But despite this, until recently many central banks did not have a good understanding of how prices behaved. Most modern monetary policy models are based on simple theoretical assumptions about the evolution of prices, and calibrated against aggregate price indices when empirical foundations are required.

However, a growing body of literature around the world suggests that this approach is likely to be very misleading. Direct studies of how individual prices behave at the microeconomic level have consistently shown that the macro models that policymakers employ yield misleading results. They fail to match the actual pattern of price-setting that is evident from individual prices, and can potentially lead to policy errors.

One country where this research has lagged behind is the United Kingdom. As such, this context statement sets out key results and findings from a collection of public works that looks at the behaviour of individual prices within the UK economy, and the implications of these results for monetary policy models and policymakers alike.

This context statement links together key results from a number of published articles to detail new evidence on the behaviour of UK prices, and the implications that evidence has for monetary policy and different pricing models. In particular, it draws upon two articles

that were published in *The Economic Journal* during 2012 (Bunn and Ellis, 2012a and 2012b). These original articles examine the behaviour of individual UK prices, using data that underpin official estimates of consumer and producer price inflation and supermarket scanner data sourced from a private sector data provider. They are the first empirical investigation and examination of individual UK consumer prices, and provide new evidence on how individual producer prices behave, making an original and important contribution to the literature. As with all the jointly authored public works included alongside this context statement, all co-authors have attested that I made an equal and significant contribution to the research.

The statement also draws upon the more detailed results that were included in the longer (Bank of England) working paper versions of the papers underpinning the *Economic Journal* publications, namely Ellis (2009a), Bunn and Ellis (2010) and Bunn and Ellis (2011). In particular, it references some of the unique findings in Ellis (2009a), which had the advantage of using higher frequency weekly data as opposed to monthly official data. The research sourced private-sector data from UK supermarkets, following in the footsteps of US research based on scanner data from stores. As such, it makes an original contribution to the literature, and also addresses the important issue of how data frequency can affect estimates of price duration. In addition, I propose a new approach for identifying and addressing temporary price changes, which offers a new way of cross-checking other techniques. Like many central bank research series, the Bank of England's Working Paper series is externally refereed, and authors have to address comments from the editors and referees (and pass other internal quality hurdles) in order for work to be published.

The statement also draws upon Mumtaz *et al* (2009), another paper from the Bank of England's refereed series with two co-authors. This paper, initiated at the same time as the pieces which eventually saw publication in *The Economic Journal*, looks at how multiple price measures can be modelled and forecast in a single consistent framework. It follows previous US research in the same field, applying the modelling technique to UK data for the first time. In addition, we propose and demonstrate an innovative strategy for identifying the model, linked with recent developments in vector autoregression (VAR) work.

Finally, the statement draws on two other public works. The first is a 2009 paper published in *The Business Economist*, which was one of three papers shortlisted for the Society of Business Economist's annual Rybczinski Prize (Ellis, 2009b). This paper, which was written for a non-technical audience, draws out some implications for policymakers from the observed frequency of price changes, linking with past work on monetary policy. The final public work is a recent article in *World Economics* (Ellis, 2012) – again written for a non-technical audience – that provides detail behind the collection, aggregation and construction of macroeconomic price indices in the United Kingdom, discussing current differences and pitfalls.

The remainder of this context statement is set out as follows. Chapter 2 provides a broad overview of the literature in this area, detailing the development of modern macroeconomic models of monetary policy, and the shift towards independent inflation-targeting central banks. It highlights results from other countries in this field, and sets up some of the practical issues concerning the microeconomic analysis of prices. Chapter 3 then describes the unique datasets from the ONS and a private sector data provider that

were employed to fill the gap in the literature and conduct similar analysis for the United Kingdom. Importantly, because the underlying price data were highly sensitive and confidential, this required careful negotiation and compliance with strict access arrangements. No one else has accessed and used this range of data in other research, and these unique data are a key strength of the analysis. Chapter 4 then summarizes results from the data analysis, finding evidence of considerable heterogeneity in pricing behaviour at the microeconomic level that does not conform either to standard theoretical structures or the macro models normally employed by policymakers. There are some key implications for policymakers, most notably in terms of the optimal response to economic shocks, which is relevant given the current conjuncture. The Chapter then outlines a new modelling approach that is capable both of capturing the underlying heterogeneity in the data and generating a tractable model for policymaking purposes. Finally, Chapter 5 concludes. Copies of all of public works included in this submission follow the conclusion of the context statement.

Chapter 2 Literature review

2.1 *After the Phillips curve: the development of modern monetary economics*

Ever since Phillips' famous 1958 *Economica* paper looking at the relationship between UK unemployment and nominal wages, understanding inflation has been a key objective for economists. Samuelson and Solow (1960) swiftly produced similar research for the United States, and 'traditional' Phillips curve analysis building on this work soon became the workhorse mechanism for understanding the dynamics of inflation. However, criticisms of this framework (Friedman, 1968) and the experience of the 1970s painfully illustrated the lack of a long-run trade off between the nominal and real sides of the macroeconomy. This led to acceptance that the short-run trade-off between prices and volumes was not structural in the sense of the famous critique from Lucas (1976). But the role of price adjustment in macroeconomic developments was still a source of some debate (Gordon, 1981). Neoclassical models typically emphasised flexible prices, while Keynesian models often assumed some degree of sticky prices, with the result that markets were not always in equilibrium.

A key short-coming of the Keynesian approach was the absence of any theoretical underpinning for price stickiness: in some models, prices were simply exogenously fixed (Malinvaud, 1977). To address this shortcoming, research on inflation dynamics focused on small models with explicit microeconomic foundations, typically assuming optimising behaviour among agents and imperfect competition or knowledge. One of the most famous micro-founded models is the 'islands' model of Lucas (1973), where businesses have

imperfect knowledge of the price level and rationally estimate it on the basis of the price of their own good, thereby solving a signal extraction problem. This can generate a short-run Phillips curve of the generic form:

$$\pi_t = E_{t-1}\pi_t + \vartheta(y_t - \bar{y}_t) \quad (1)$$

Where π denotes the inflation rate, E is the expectational operator, y is output and \bar{y} is trend output.¹ Inflation in this model therefore depends on past expectations and the output gap.

One drawback of the islands model is that it did not incorporate any nominal rigidity – although expectational errors relate to deviations of output from trend, in principle prices can adjust continuously. In fact, some degree of nominal rigidity in the economy is often assumed, so that selling prices in product markets are ‘sticky’. This stickiness is normally assumed to reflect some sort of constraint that prevents prices from adjusting instantaneously or costlessly. Fisher (1977) introduced nominal rigidity by assuming that prices were predetermined; they are assumed to be set for several periods by contracts that specify prices for each period. Other work focused on directional barriers, and in particular downward nominal rigidities: Yates (1998) provides a good discussion here. However, these frameworks, like that of Lucas (1973), typically still allow continuous price adjustment.

This presented an empirical challenge, as a wide body of work during the 1990s demonstrated that monetary policy could certainly exert significant influence on the real

¹ Note that shocks are omitted for simplicity. Okun’s ‘law’ (from Okun, 1962) is often used to substitute the deviation of output from trend for the gap between actual and equilibrium unemployment.

economy in the short term. One influential paper was the seminal piece by Romer and Romer (1989), which used historical evidence on large monetary shocks that were not triggered by deviations in output. Using post-war US experience, the authors found that the Federal Reserve's actions had a significant (and persistent) impact on unemployment, and that this result was robust to a number of different specifications. In order for nominal policy rates to impact on real variables in this manner, even in the short term, some form of nominal rigidity was required to let movements in nominal policy rates to feed through to short-term real interest rates.

Subsequent work in this area included Bernanke and Blinder (1992), who examined the transmission channels of monetary policy, Christiano *et al* (1998) who examine the impact of monetary policy shocks based on vector autoregressions (VARs), and Rotemberg and Woodford (1999) who examine the cyclical behaviour of prices and costs. Bernanke *et al* (1997) present further evidence that the monetary policy can have important effects on real activity. This suggested that the appropriate role for monetary policy, given the long-run neutrality of policy with respect to the real economy, was to minimise the variability of inflation around some steady-state (or target) rate and the variability of output (or employment) around a sustainable path (Rotemberg and Woodford, 1997). In doing so, the monetary policy maker is implicitly choosing a trade-off between the volatility of inflation and the volatility of output.

2.2 *The role and framework of monetary policy*

This perspective then gave rise to various debates about the optimal role and institutional arrangements of monetary policy. Given the accepted lack of any long-run trade-off between the nominal and real sides of the macroeconomy, the main role of monetary policy was seen as providing a nominal anchor to the economy – a beacon against which relative prices and policy actions could be benchmarked. During the 1980s some monetary regimes focused on controlling the money supply. Yet while this was reasonably successful in the case of the German Bundesbank, other countries such as the United Kingdom did not find monetary targets as useful. In part, this was driven by instability in the relationship between the money supply and inflation, or other macroeconomic variables – the velocity of money was variable and volatile. Although Friedman and Schwartz (1963) carefully identified and illustrated the impact of exogenous shifts to the money supply, more recent evidence such as Estrella and Mishkin (1997) and Stock and Watson (1999) produced conflicting and unstable results for the influence of money growth on inflation.

Many believe this instability is a structural feature of the economy, and that the relationship between money and inflation may only hold at long frequencies in many instances (see Benati, 2005b for UK evidence). However, Issing (1997) notably argued that velocity was stable in Germany due to the stability of policy.

The difficulties in attempting to focus on measures of the money supply led many countries to adopt a different approach. Broad money supply is a relatively technical economic concept that may not be intuitively understood by ordinary economic agents: it is not

natural to benchmark your own selling price against an intangible data series that includes short-term bonds and claims on banks from repurchase operations (repos). On the other hand, inflation data had been collected and monitored for several decades in a number of countries. Although cross-country evidence suggested a strong relationship between the pace of money growth and price inflation (McCandless and Weber, 1995), uncovering stable short-term relationships proved difficult. As such, monetary policy authorities became more concerned with the ultimate goal of price stability, rather than the intermediate goal of targeting the money supply (King, 2002). Pétursson (2004) describes the adoption of inflation targets around the world in more detail.

Based on the previous UK experience of inflation, some authors thought that the ability of a central bank to hit even a broad target would be low (Haldane and Salmon, 1995), with one even suggesting that the central bank would face a trade-off not just between output and inflation, but also ‘credibility and humility’ (Haldane, 1995). In the event, the performance of inflation targeting, particularly during the 1990s, was remarkably good (Sterne, 1999), and substantially better than might have been expected based on past experience. Benati (2005a) provides a good summary of the UK experience: taking a 400 year perspective, he finds that the inflation targeting regime was – at least at the time of the research – characterised by the most stable macroeconomic environment in UK history.

Many authors, such as Mumtaz *et al* (2011), attribute this partly to the structural change that accompanied the adoption of inflation targeting, including the anchoring of inflation expectations. However, more benign economic conditions are also likely to have played a role – until recently, many economies had enjoyed a long period of relative economic

stability, which some have termed the 'Great Moderation' (Stock and Watson, 2002). Davis and Kahn (2008) ascribed the reduction in macroeconomic volatility to productivity and efficiency enhancements and the shift in production and employment from goods to services. However, Benati (2008) suggests a dominant role for 'good luck' in fostering the stable macroeconomic environment in the United Kingdom. In the wake of the 2007/8 financial crisis and 'Great Recession', with the benefit of hindsight luck certainly seems to have played a greater role than might have been assumed before the crisis broke. However, such was the performance of inflation targeting that it spread rapidly around the globe. Sterne (1999) reports that, when surveyed, roughly 55% of central banks had adopted some form of inflation target or monitoring range for inflation in 1990. By 1999, that percentage had risen to 96%.

At the same time, past economic research had noted the problem of time inconsistency facing policymakers. Kydland and Prescott (1977) demonstrated that even a rational and forward-looking government, which wanted to maximise the welfare of its citizens, would announce one plan for policy and then re-optimize and change it at a later date if it was given a chance to do so. As such, governments are unable to make binding commitments and suffer a credibility problem. Barro and Gordon (1983) made similar observations. This led Rogoff (1985) to propose that governments should delegate monetary policy to an independent and conservative central bank in order to reduce inflationary bias. Cukierman (1994) and Berger *et al* (2001) found that central bank independence was indeed associated with lower inflation. Typically, policy decisions were handed over to groups of people rather than individuals; evidence suggests that the former typically outperformed the latter (see Blinder and Morgan, 2000, and Lombardelli *et al*, 2005).

Alongside the advent of the new frameworks, economists were also interested in describing how policymakers set monetary policy. Previous work, notably that of Friedman (1960), had looked at exploiting the Fisher relationship between the money stock, velocity of money and nominal output² in order to generate a simple rule for the growth rate of the money stock. This was subsequently developed and empirically tested by the likes of McCallum (1988).

An early contribution from Taylor (1993) noted that the past behaviour of US policy rates could be well described by a simple ‘rule’ relating to deviations of output from trend and deviations of inflation from its desired level.³ One important adaptation to this rule was the addition of lagged policy rates in order to take account of the ‘smoothness’ of policy rates, which is especially important in frameworks where expectations play a key role (Woodford, 2003). Other variants and developments of the ‘Taylor rule’ for monetary policy soon appeared, including the ‘Taylor principle’, which is based on the observation from a formulation of the Taylor rule that central banks can stabilise the macroeconomy by increasing policy rates by more than one-for-one in response to upside inflation shocks (Davig and Leeper, 2005). Clarida *et al* (2000) cite the close correspondence between actual monetary policy rates and those implied by Taylor Rules as an important contributor to the stability of inflation in the 1980s and 1990s. Orphanides (2007) provides a good summary of the development and characteristics of Taylor rules.

However, several authors have expressed concerns about mechanistically following such simple policy frameworks. In fact, the arguments about rules versus discretion have

² This is often decomposed into the price level and real output.

³ Henderson and McKibbin (1993) made a similar observation.

persisted for several decades: Guitan (1994) provides a useful summary. Orphanides (2003) demonstrates that the Taylor rule could have resulted in inferior macroeconomic performance during the 1970s. And Bernanke *et al* (1999) prefer to describe inflation targets more as a framework than a rule, and argue they should be considered as 'constrained discretion'. With the benefit of recent central banking experience, this perspective seems uniquely appropriate. One of the lessons from the recent financial crisis, the so-called 'Great Recession' and the accompanying policy responses is that it can be an advantage to have creative policymakers that consider a range of options before they are needed. Perhaps the best example here is given by Bernanke (2002); over the past five years the unorthodox monetary policies outlined therein have been employed in several developed economies including the US, UK, Japan, Switzerland and the euro area.

2.3 *Developing structural models for policymakers*

Despite the shift in power towards independent central banks, monetary policy makers still needed good structural models that could match the empirical behaviour of inflation and impact of monetary policy. The problem was therefore how to build micro-founded economic models that matched the empirical evidence for the role of monetary policy in influencing output in the short term. Importantly, this had to incorporate some degree of nominal rigidity, thereby driving a wedge between nominal and real interest rates and giving rise to non-neutral effects from monetary policy in the short term (Goodfriend and King, 1997). In seeking to resolve this problem, several theoretical mechanisms have been proposed to incorporate nominal rigidities that limit the frequency of price adjustment. They can be broadly categorised under one of two headings: time-dependent or state-dependent pricing.

In a time-dependent model, infrequent price adjustment is specified in the original micro-foundations of the model. The likelihood of price adjustment does not depend on a particular firm's sales or the state of the economy, but instead on the time since the previous price change. Perhaps the most commonly cited mechanism is that of Calvo (1983), where firms have a fixed probability of changing their price in each period – in particular, the probability of a price change does not depend on when the previous price change occurred. An alternative time-dependent model is one of staggered contracts, in which prices are fixed for the duration of a contract and contracts overlap so that they do not all start and end at the same time (Taylor, 1980). Typically, these models assume that firms are homogeneous. More recent contributions, such as Gali and Gertler (1999) and Carvalho

(2006), have allowed some heterogeneity in the frequency of price changes, in no small part to try to better match empirical evidence on the mixed frequency of price changes (Alvarez *et al*, 2005).

Other versions of time-dependent models have also sought to move away from a homogeneous framework. Aoki (2001) introduced a two-sector economy, characterised by one sector where prices change continuously and another sector where prices are sticky. Wolman (1999) proposes a truncated Calvo model, in which all firms must adjust prices at some horizon, so that price durations of an arbitrarily long length are excluded. And Bonomo and Carvalho (2004) assume that the frequency of price changes is chosen optimally by firms, thereby making time-dependency endogenous.

In contrast to time-dependent models, in a state-dependent pricing model the decision to change prices depends on the state of the economy and the market faced by the firm. In order to generate nominal rigidities in these frameworks, firms are typically assumed to face some cost or barrier to adjusting their price. Sheshinski and Weiss (1977) assume that a fixed real charge is associated with every price change, and as such optimal price-setting behaviour is characterised by a sequence of finite intervals during which the nominal price is held constant, interspersed by discrete price adjustments. This is known as the (s,S) price adjustment policy, where companies change their actual selling prices if the optimal price falls below the lower bound of s or rises above the upper bound of S .

Mankiw (1985) developed this mechanism further, showing that under certain conditions these small 'menu costs' – based on the notion that restaurants have to re-print menus or

businesses have to re-print catalogues – could generate potentially large welfare losses by driving selling prices away from their optimal level. This complemented previous work from Okun (1981). Rotemberg (1982) introduced convex costs of adjustment for firms that wished to change prices, based on the observation in Stiglitz (1979) that, under imperfect competition, customers will tend towards firms with relatively stable price paths. Dotsey *et al* (1999) further develop the menu cost model so that each firm faces a different cost over time, which is drawn independently from a continuous distribution. As such, some firms adjust their price within each period.

Recent research has also considered the potential role of ‘information stickiness’ as a means of introducing rigidities. The simple insight in this strand of the literature is that expectations about inflation will determine the extent to which movements in nominal interest rates translate into movements in real interest rates and, hence, real aggregate demand. Mankiw and Reis (2002) emphasise that inflation expectations may be sticky as a result of price setters not having the incentive to obtain the complete and up-to-date information necessary to form rational expectations of inflation, which could then manifest as sticky prices. Reis (2006) developed this work, noting that producers may be rationally inattentive when confronted with many different signals.

In the event, by far the most popular mechanism for incorporating price stickiness at the microeconomic level has been the so-called Calvo pricing model (based on Calvo, 1983). In this framework, because individual companies have an exogenous probability of being able to change prices in any given period, those companies that change their prices have to consider what future prices are (and will be) optimal in case they don’t get the chance to

change prices again for some time. The simplest form of Calvo (1983) pricing gives rise to the so-called ‘New Keynesian Phillips Curve’ (hereafter NKPC). The significant advance of the NKPC over the Lucas ‘islands’ model is that current inflation depends on the expectation of future inflation, rather than inflation depending on its past expectation. The standard NKPC model can be written as:

$$\pi_t = \beta E_t \pi_{t+1} + \tau(mc_t - \overline{mc}_t) \quad (2)$$

where mc denotes marginal cost.⁴ Popular measures for the deviation of marginal cost from its steady-state value are the labour share (Gali *et al*, 2001) and the output gap (Neiss and Nelson, 2005). However, subsequent research suggests that these proxies may be a poor gauge of true marginal cost; recent evidence suggests this is likely to be the case for the United Kingdom (Ellis, 2006) and France (Dobbelaere and Mairesse, 2007). In addition, it can be very difficult for policymakers to accurately gauge the output gap in real time, as illustrated by Orphanides *et al* (2000) and Nelson and Nikolov (2001). In part this relates to data uncertainty issues, as documented in Castle and Ellis (2002). But measures of potential supply and the output gap may also struggle to accurately take account of movements in multifactor productivity or technical progress if these series exhibit a stochastic element (Ellis, 2006).

Despite these concerns, the NKPC was popularised by a series of papers over the past twenty-five years, such as Clarida *et al* (1999) and Gali and Gertler (1999). By combining the NKPC with other key economic relationships, economists were able to build and estimate

⁴ Alternative derivations are possible. For instance, Bakhshi *et al* (2004) start from a state-dependent pricing framework to derive a generalised Phillips curve that nests the NKPC as a special case.

small macroeconomic models that were supposed to capture the key dynamics of an economy, while at the same time exhibiting solid microeconomic foundations. These models are known as Dynamic Stochastic General Equilibrium (DSGE) models, and were first introduced in a New Keynesian framework by Rotemberg and Woodford (1997); Gali (2008) provides a more recent presentation. Critically, Yun (1996) showed the importance of the assumption of exogenous price adjustment, which delivers significant analytical tractability in DSGE models.

2.4 *Testing the empirical performance of NKPC models*

A key test of the NKPC model was its ability to match the time-series properties of inflation that were observed in macroeconomic data, such as the dynamic response of inflation to monetary policy changes. These empirical responses are typically estimated using VAR models, which typically relate a small set of macroeconomic time series – GDP, inflation and interest rates – to their own lags. In order to identify economic shocks, the reduced-form model residuals are transformed to allow a ‘structural’ economic interpretation to be placed on the resulting impulse responses. As discussed later, a critical issue with VAR models is how precisely to make this transformation. Several authors (for instance Canova and de Nicolò, 2002 and Uhlig, 2005) have criticised the standard Cholesky identification method, where variables are ordered according to how shocks are believed to be transmitted through the economy.

A common result from these VAR models is that a tightening of monetary policy has either little immediate impact on inflation, or generates a small increase in inflation in the short term. This counterintuitive response – tighter monetary policy would normally be expected to bear down on inflation – is the so-called ‘price puzzle’, as noted by Sims (1992) and labelled by Eichenbaum (1992). However, several authors including Giordani (2004) and Castelnuovo and Surico (2006) believe that the price puzzle is likely to reflect misspecification in the underlying VAR model, rather than being a genuine macroeconomic phenomenon.

Subsequent to the near-term response, the monetary policy tightening leads to a steady decline in the price level lasting beyond two years, relative to where the price level would have been without the policy tightening. In other words, a rise in interest rates has a persistent impact on the aggregate inflation rate after about six months. This result soon became a benchmark against which other models were tested: a useful model of inflation should be able to explain the short-run absence of a response in inflation to a monetary policy tightening, and the persistent response beyond six months.

Regrettably, the first NKPCs failed to capture the properties of aggregate inflation suggested by these VAR models. Chari *et al* (1996) and Edge (2000) show that NKPC models did not seem to be able to generate enough persistence in the response of output and inflation to economic shocks. Taylor (1999) and Guerrieri (2002) also noted the NKPC's so-called 'persistence problem' in failing to match high observed persistence in the empirical data. Lendvai (2006) also showed that the response of inflation to monetary policy movements was not persistent enough.

A variety of ad hoc adjustments were subsequently introduced to the NKPC model, such as 'rule of thumb' price setting behaviour. These adjustments often incorporate lagged inflation into the NKPC, which helps it fit the empirical data better (as shown for instance by Clarida *et al*, 1999). At the same time, such ad hoc adjustments clearly violated the original intention of establishing wholly micro-founded models. As such, more formal mechanisms such as automatic indexation – for instance where firms are assumed to index their prices using lagged inflation rates when prices are not adjusted optimally – have also been proposed (Christiano *et al*, 2005).

Despite their widespread use in the academic literature, several authors have criticised the use of NPKC models. Most notably, Rudd and Whelan (2005) argue that these models fail to provide a good match to the empirical inflation process, compared with simpler econometric models, suggesting that the NKPC may fail to provide a good guide to policymakers.

2.5 *Microeconomic evidence on the behaviour of prices*

Perhaps the most important result arising from NKPC models – and, ultimately, a devastating critique – relates to the very micro-foundations that they are based on. The underlying assumption of Calvo pricing, embedded in most NKPCs, is that each firm has a fixed probability of changing prices each period: so, each period, a constant fraction of companies will actually change their prices. Based on estimated NKPCs, it is therefore possible to work out what the implied probability of changing prices is and, hence, how long (on average) prices are held fixed before they change. The common result from estimated NKPCs is that firms, on average, change their prices once every five to six quarters (Gali and Gertler, 1999), although some estimates suggest that prices change only once every two years (Smets and Wouters, 2003).

This compares poorly with evidence on price-setting from direct observation of companies and prices. Various surveys of firms, such as Blinder *et al* (1998) for the United States and Fabiani *et al* (2005) for the euro area, have suggested that the median firm changes its main price around once a year. Since the early work of Blinder *et al* (1998), numerous other studies have surveyed firms directly to try to uncover price adjustments, including Amirault *et al* (2005) for Canada, Aucremanne and Collin (2005) for Belgium, and Alvarez and Hernando (2007) for Spain. Similar surveys have also been undertaken in the United Kingdom, most notably by Hall *et al* (2000) and Greenslade and Parker (2012). Often, these surveys chime with the original results from Blinder *et al* (1998), in that they find that the median firm adjusts prices once a year. However, in the cases of Canada (Amirault *et al*, 2005), Luxembourg (Lünneman and Mathä, 2006) and the United Kingdom (Hall *et al*, 2000),

the median number of price changes is somewhat higher, at two or three a year rather than just one price change per year.

At the same time, many direct surveys of businesses such as Hall *et al* (2000) and Fabiani *et al* (2005) tend to find that prices change with different frequencies in different sectors. In particular, prices appear to be reviewed and changed less frequently in the services sector (as a whole) than in the manufacturing sector. Meanwhile, prices in some specific parts of the economy, such as retailing, can sometimes change far more frequently than in other sectors. Aside from positing the existence of different groups of price-setters (Alvarez *et al*, 2005), little has been done to formally incorporate this observation of different adjustment frequencies into a tractable macroeconomic model.

This discontinuity between survey evidence and NKPC models led to a raft of research looking at how individual prices change. These studies typically use large databases of individual price quotes to examine how prices behave at the microeconomic level. One notable contribution is that of Bils and Klenow (2004) for the United States. They found evidence that prices changed more frequently than the earlier survey evidence suggested. Even when the importance of sales and special promotions in explaining frequent price changes in the US economy is recognised – where the median frequency of price changes excluding sales is roughly half what is when sales are included, as Nakamura and Steinsson (2008) illustrate for producer prices – the frequency of price adjustment is significantly higher than both surveys of firms and NKPC models suggest. Other US research also supports the view that prices are more flexible at the micro-level than the NKPC implies. Other differences are also evident: for instance, Boivin *et al* (2007) find that the degree of

persistence in disaggregated price data is much smaller than in the aggregate measures that NKPCs focus on.

Another stream of the literature focuses on higher-frequency data. By their very nature, official measures of price levels – either at the macroeconomic or microeconomic level – will tend to be constrained by frequency, as noted in Ellis (2009a). It is rare for statistical offices to collect, aggregate and publish price data more than once a month. By definition, this implies that – at most – prices will be recorded as changing twelve times a year. However, in some sectors prices obviously change more frequently than this; financial markets are a good example, as prices can change several times within a single day.

Another instance where prices may change frequently is in supermarkets. There is a growing body of work which exploits scanner data from major retail outlets, where prices are recorded at the point of sale. This research includes Pesendorfer (1998) and Chevalier *et al* (2000) for the United States, as well as Kehoe and Midrigan (2007) who explicitly focus on the frequency of price changes and the impact of temporary discounts. These papers typically show that prices change very frequently in supermarkets and similar outlets – often more than once a month. One important consideration here is the treatment of temporary discounts (or sales) in the micro data: Eichenbaum *et al* (2008) have argued that such temporary deviations in prices may have little relevance or significance for monetary policy. I return to this later; for now, it is worth noting that even after temporary deviations in price are excluded, the frequency of price change is much higher than implied by NKPC models (Kehoe and Midrigan, 2007). Yet again, there is an obvious discontinuity between empirical evidence and the findings of estimated NKPC models.

These findings spurred numerous other studies looking at the observed frequency of price adjustment at the microeconomic level, particularly within Europe. One driving force behind this research effort was the euro area inflation persistence network (IPN), which saw researchers from across the continent exploit new access to large microeconomic datasets to uncover direct evidence on the frequency of price changes. Notable IPN studies include Aucremanne and Dhyne (2004) for Belgium, Hansen and Hansen (2006) for Denmark, and Veronese *et al* (2006) for Italy. In addition, similar projects elsewhere around the world covered countries as diverse as Mexico (Gagnon, 2006), Japan (Saita *et al*, 2006) and Sierra Leone (Kovanen, 2006). In some instances, this work has then been developed to relate it to other economic trends: for instance, Abraham *et al* (2006) use a panel approach to uncover evidence on the impact of globalisation on price and wage setting in Belgium.

The vast majority of this microeconomic investigative work concentrated on consumer, rather than producer, prices. But, where such data were available, the incidence of changes in producer prices was also considered, although this work was more concentrated within European countries. Examples include Dias *et al* (2004) for Portugal and Gautier (2006) for France.

Table 2.1 provides a summary of results from past microeconomic research on consumer prices, in particular focusing on the average percentage of prices that are observed to change each month in the micro data, drawing partly upon Alvarez (2007). Table 2.2 presents analogous results for producer prices. Across all the studies, the average frequency of monthly price changes is around 20% for consumer prices; for producer prices, it is around 22%. These estimates suggest an average duration for consumer prices of

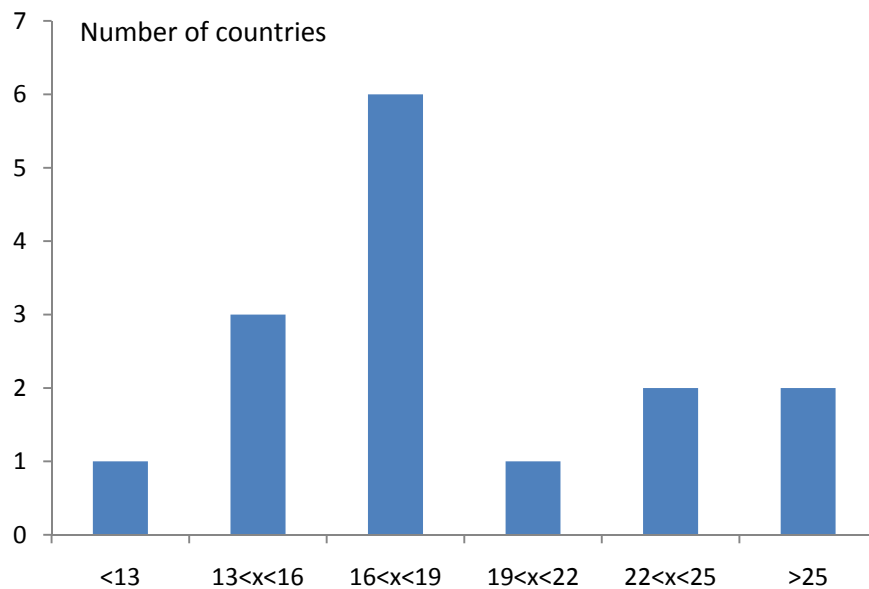
around 5 months, and for producer prices of around 4½ months. Both of these results suggest that there is a significantly greater degree of price flexibility at the microeconomic level than is implied by modern price models such as Gali and Gertler (1999) and Smets and Wouters (2003).

Table 2.1: Summary of past microeconomic investigations into consumer price changes

Paper	Country	Sample	Frequency of monthly price changes (%)
Baumgartner <i>et al</i> (2005)	<i>Austria</i>	1996-2003	15.1
Aucremanne and Dhyne (2004)	<i>Belgium</i>	1989-2001	16.9
Hansen and Hansen (2006)	<i>Denmark</i>	1997-2005	17.3
Dhyne <i>et al</i> (2006)	<i>Euro area</i>	1996-2001	15.1
Vilmunen and Laakkonen (2005)	<i>Finland</i>	1997-2003	16.5
Baudry <i>et al</i> (2007)	<i>France</i>	1994-2003	18.9
Hoffmann and Kurz-Kim (2006)	<i>Germany</i>	1998-2004	11.3
Gabriel and Reiff (2007)	<i>Hungary</i>	2002-2006	19.9
Veronese <i>et al</i> (2006)	<i>Italy</i>	1996-2003	10.0
Saita <i>et al</i> (2006)	<i>Japan</i>	1999-2003	23.1
Lünnemann and Mathä (2005)	<i>Luxembourg</i>	1999-2004	17.0
Jonker <i>et al</i> (2004)	<i>Netherlands</i>	1998-2003	16.5
Dias <i>et al</i> (2004)	<i>Portugal</i>	1992-2001	22.2
Kovanen (2006)	<i>Sierra Leone</i>	1999-2003	51.5
Alvarez and Hernando (2006)	<i>Spain</i>	1993-2001	15.0
Bils and Klenow (2004)	<i>United States</i>	1995-1997	26.1
Nakamura and Steinsson (2008)	<i>United States</i>	1988-2005	26.5

Table 2.2: Summary of past microeconomic investigations into producer price changes

Paper	Country	Sample	Frequency of monthly price changes (%)
Cornille and Dossche (2006)	<i>Belgium</i>	2001-2005	24
Vermuelen <i>et al</i> (2007)	<i>Euro area</i>	varied	21
Gautier (2006)	<i>France</i>	1994-2005	25
Stahl (2006)	<i>Germany</i>	1997-2003	22
Sabbatini <i>et al</i> (2006)	<i>Italy</i>	1997-2002	15
Dias <i>et al</i> (2004)	<i>Portugal</i>	1995-2001	23
Alvarez <i>et al</i> (2008)	<i>Spain</i>	1991-1999	21
Nakamura and Steinsson (2008)	<i>United States</i>	1988-2005	25

Figure 2.1: Distribution of monthly consumer price change frequencies across countries

Source: Based on Table 2.1.

At the same time, the degree of variation across countries is striking. Figure 2.1 plots the distribution of the average frequency of price changes across the countries reported in Table 2.1. There is one notable outlier (Sierra Leone), and the average frequency of price changes exhibits some clustering across economies at around 16-19 months. Across the studies of individual European economies, the average percentage of consumer prices changed each month is 16.4, implying an average price duration of around 6 months. In the US, around a quarter of consumer prices change each month, implying an average duration of around 4 months. Interestingly, the divergence between the US and European results is much smaller in the case of producer prices than for consumer prices. In part, this could reflect the fact that producer prices are more likely to correspond to export goods; and as such, European and US competitors' price-setting behaviours may be more closely related. Alternatively, it could suggest that price rigidities between the production and retail sectors are somewhat more prevalent in Europe.

2.6 *Identified gaps in the literature*

Despite the wide range of past work that has examined the empirical behaviour of individual or microeconomic prices, there are still clear issues that need to be addressed. The original public works included in this submission attempt to fill these gaps.

First, despite much research in other countries that has looked at microeconomic evidence on the behaviour of prices, such studies have not recently been conducted in the United Kingdom. Some qualitative evidence does exist, from the past surveys of firms' pricing behaviour cited previously. But the only past research to directly examine the empirical behaviour of individual prices that I am aware of was limited and very dated work by Godley and Gillion (1965), which looked solely at producer prices. Given the substantial structural changes to the UK economy and policymaking environment since that time, further research was required. As a small, open economy with an independent inflation-targeting central bank, this oversight had to be addressed given the central importance of consumer prices in today's policymaking framework.

Second, despite difficulties with current approaches, researchers have a continued desire to develop useful models of inflation for policymaking and other purposes. Given the past research in this field discussed earlier, one key gap in the literature is how to address the problem of simultaneously capturing the observed behaviour of inflation at the macroeconomic level, while at the same time recognising and encompassing the observed degree of price flexibility at the microeconomic level. While there has been some recent

research in this area for the US economy, there was no comparable work looking at the United Kingdom.

Against this backdrop, the remaining sections of this context statement describe recent original research that investigates the behaviour of UK prices at the microeconomic level. Subsequently, it considers the implications of the analytical results for the setting and framework of monetary policy, and then explores a new modelling approach that allows policymakers to take account of differences between the microeconomic and macroeconomic behaviour of prices.

Chapter 3 New microeconomic data for UK prices

3.1 Introduction

Chapter 2 established that, despite the central role of inflation targeting in UK economic policymaking, there was a notable gap in the relevant economic literature. In particular, very little prior work had examined the behaviour of individual prices in the UK economy, in terms of directly observing how those prices evolve over time. At the same time, this meant that the models frequently used by policymakers could be seriously flawed. Research for other countries has established that the microeconomic behaviour of prices is often very different from the behaviour assumed by ‘micro-founded’ economic models that policymakers often employ.

A key contribution of this research is therefore to examine the behaviour of individual prices within the United Kingdom. Most existing analysis of price-setting and pricing models relies on aggregate price indices, either for the manufacturing or retail sectors. However, in line with results for other countries, it is also critical to consider microeconomic data in order to uncover whether inferences from aggregate data are genuinely evident in individual prices. Based on research elsewhere, it could well prove to be the case that aggregate price indices do not provide a good guide to the underlying microeconomic behaviour of prices.

One key challenge here was to find detailed datasets of microeconomic prices. Without reliable empirical data on individual prices, the analysis presented in the public works would simply not have been possible; the data were a critical precondition. As such, the data

represent a unique aspect of the research, as to the best of my knowledge no analysis had recently been conducted looking directly at the microeconomic behaviour of prices in the United Kingdom. The difficulties in identifying and accessing these detailed datasets have probably contributed to the lack of previous research in this field. Armed with these data, it was then possible to examine and compare the empirical frequency and magnitude of individual prices changes within and across sectors; to construct conditional probabilities of prices changes and hazard functions; and to gauge how individual price data relate to the macroeconomic aggregates that are more typically examined.

After setting out some background on different measures of price indices in the UK economy, this Chapter then details the three unique datasets that were used to analyse the behaviour of UK prices at the microeconomic level. One particular point of note is the distinction within these datasets between ‘temporary’ price changes and other changes in selling prices, which has proved to be critical in other research.

3.2 *The importance of different measures of prices*

Inflation is a key economic indicator for policymakers. But one of the issues that inflation targeting central banks have to wrestle with is distinguishing between relative price shifts, and generalised inflationary pressure.

In any normal, functioning market economy, the prices of individual goods and services will change over time; the role of an inflation-targeting central bank is not to ensure that each and every price in the economy rises by 2% a year. Instead, it is to ensure that monetary policy anchors the pace of increase in the general price level of goods and services across the economy as a whole. But as technology, consumer preferences and other factors shift over time, the prices of some goods and services relative to others – or the relative price of those goods and services – should be allowed to adjust in the normal way. This allows for the usual function of price signals in a market economy, enabling the efficient allocation of resources in the absence of market failures such as externalities.

Provided agents' inflation expectations are well-anchored, monetary policy makers should not respond to these one-off movements in individual (relative) prices. As individual prices increase in one part of the economy, it is possible that prices may decrease elsewhere as demand and spending shifts from one sector to another, leaving the average price level little changed. In practice, however, timing and other issues mean that these relative price shifts could still influence the path of measured inflation.

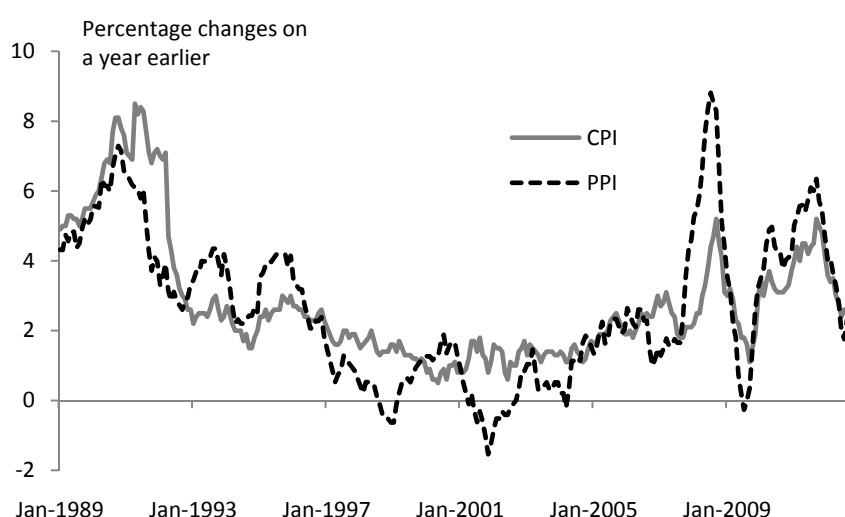
In contrast, if policymakers detect generalised inflationary pressure – prices and wages moving higher throughout the economy as a whole at a faster pace than is consistent with the inflation target – then monetary policy may need to be tightened to ensure that inflation is kept under control. A key judgement for policymakers is therefore to consider whether an observed move in prices or inflation reflects generalised inflationary pressure, or just a one-off relative price shift.

In principle, generalised inflationary pressure should be evident in several different sectors of the economy and in different inflation measures. But if there is considerable heterogeneity in price setting – if prices in different sectors change with different frequencies and magnitudes than in other sectors – then policymakers may get conflicting signals from different inflation series. As such, it is important to consider not just one measure of inflation but to compare and contrast different measures; in the same vein, it is also important to compare and contrast different sources of microeconomic price data in order to uncover how heterogeneous pricing behaviour may be. The next section provides some background on the three different sources of microeconomic prices that are used in the public works included in this submission, and their individual advantages and disadvantages: official producer prices; official consumer prices; and supermarket scanner data.

3.3 Background on microeconomic price data

The most-referenced measures of inflation in the United Kingdom are published by the Office for National Statistics (ONS). In order to publish these series, the ONS collects and compiles individual price quotes from companies around the country. Two of the key measures of inflation are the change in the Consumer Prices Index (CPI), and the change in the Producer Prices Index (PPI). Both of these are shown in Figure 3.1.

Figure 3.1: Measures of UK price inflation



As might be expected, the CPI is based on price data collected from firms selling goods and services to consumers; in contrast, the PPI is based on prices collected from manufacturers that typically sell intermediate goods. However, the collection and aggregation of individual prices varies substantially between the CPI and PPI. In fact, the mechanisms by which price data are collected and aggregated are not uniform even within the CPI or PPI, and there are a number of practical issues that are outlined below.

To start with, the method of collecting consumer and producer prices varies substantially. In the case of the CPI and the corresponding retail prices index (RPI), most underlying price data are collected locally. To facilitate this, ONS price collectors go to shops around the second or third Tuesday of every month, known as 'Index Day', and record the selling prices that they observe. These locally collected data make up around two-thirds of the overall CPI by weight.⁵ The remaining prices are collected centrally by the ONS, and are typically national prices from particular companies. Around 180,000 separate price quotations are used each month. The main coverage differences between the CPI and RPI relate to owner-occupied housing costs, which are currently excluded from the former. Ellis (2012) discusses differences in weighting and methodology in more detail.

It is also important to consider the potential impact of price regulation on the behaviour of individual prices. If legal or regulatory restraints prevent firms from changing prices frequently, or by a significant magnitude, then this should be evident in the micro data. For instance, Aucremanne and Dhyne (2004) find evidence of 'forced' price synchronisation for administered prices in Belgian micro price data.

In general terms, prices in regulated sectors may change less frequently or by different magnitudes than in unregulated markets, or only change at particular times of the year, due to regulatory constraints. In the United Kingdom, for instance, the maximum permissible increase for some services is set by regulators; examples include water supply and many rail fares. In light of these regulatory practices, these types of prices often change at the same time each year, albeit sometimes by varying amounts – for instance, in the case of rail fares

⁵ One notable difference is that CPI prices for petrol and oil are averaged over the month, based on prices each Monday. In the RPI, these prices are collected alongside others on Index Day.

the size of price changes is allowed to vary by route and operator. As such, price regulations can sometimes have a more noticeable impact on the timing of individual price changes, rather than the magnitude.

A similar point can be made in relation to fiscal policy. The UK government imposes duties on a number of items such as alcohol and tobacco products, as well as petrol. More broadly, value-added tax (VAT) is charged on a wide range of products. Changes in these duties or VAT will impact on consumer prices; and as duties, in particular, are normally changed once a year in April, that could lead to a spike in price changes at that time. Similar considerations apply to rental prices, where local authorities typically review their charges once a year. Patterns in regulated prices, and more broadly taxes and duties, are therefore likely to affect the observed pattern of individual price changes.

The RPI and CPI employ detailed processes to eliminate potential outliers from the data – unusual or extreme observations that could distort the aggregate picture. Before locally collected prices are transmitted to the ONS, several checks are carried out by collectors. The observed price is compared with the price for the same product, in the same shop, in the previous month (if possible). A ‘price change’ check then warns collectors if the percentage change exceeds pre-specified limits for different items. The price will also be checked against a ‘min/max range’ determined on the type of item and derived from the latest (non-zero) price for the same product. After the locally collected data are sent to ONS, these local checks are reapplied. In addition, an outlier detection process known as the Tukey algorithm is also employed to remove outliers. ONS (2012) provides further detail on the Tukey algorithm and the other statistical processes that are employed.

The data underlying the PPI are collected in a different fashion. Instead of directly collecting observed prices, most of the raw data underlying the PPI are based on a monthly ONS survey of UK businesses that are registered for value-added tax (VAT) or pay-as-you-earn (PAYE) income tax. Roughly 4,000 businesses are sampled from a population of around 140,000 firms, based on the Inter Departmental Business Register (IDBR). The sample is stratified by sales and product classes. In response to the survey, firms return input (cost) and factory gate (output) price quotes to the ONS, with around 6,750 price quotes provided for home sales. The PPI data are based on a 'basic price' concept, which should exclude VAT as well as duties and taxes on the goods sold. Apart from computers, where a hedonic model is used to adjust for changes in quality, the survey relies on advice from respondents when the specification of a particular item changes; the goal is that only the 'pure' price change is recorded. This means that, unlike the CPI/RPI, the PPI is far more reliant on reported (as opposed to directly observed) microeconomic price data. In marked contrast to the CPI/RPI, there is no formal routine for detecting/treating outliers. Instead, atypical and extreme returns are typically identified as part of the general validation of survey responses, and businesses are contacted to check accuracy in these instances. Ellis (2012) provides more detail on the collection and aggregation of individual price data.

One consequence of CPI/RPI and PPI data collection is that the highest possible data frequency is monthly. This means that, at most, the prices that are collected can change 12 times during any single year – that is, once each month. This is an important constraint when considering underlying economic structures such as the degree of price flexibility. As noted in Chapter 2, existing evidence from higher-frequency data suggests that, in some

instances, prices may change more frequently than once a month. As such, the collection of monthly data could potentially overstate the implied stickiness of prices.

In order to investigate this potential shortcoming, it was also necessary to consider other data sources. In particular, past US work based on scanner data from retail outlets, such as Chevalier *et al* (2000) and Kehoe and Midrigan (2007), appeared to offer a useful line of enquiry. Unlike the microeconomic pricing data that underpin official price indices, the hope was to uncover a higher-frequency data set.

Rather than approach a UK retailer to ask for access to data, I instead decided to approach a collector and collator of price and volume data across different retailers. The Nielsen Company is a global leader in providing sales and marketing information, audience measurement, and business products and services. Among other services, Nielsen regularly supplies their clients with bespoke analysis of sales trends and promotional impacts, by monitoring and analysing sales data at an extremely detailed level. In order to provide this service to its clients, Nielsen collects barcode-level data from Electronic Point of Sale (EPoS) checkout scanners at up to 65,000 supermarket and convenience stores in Great Britain. The data collected cover sales values, volumes sold and promotional activities for a wide range of products and items.

There are some key advantages of this bespoke Nielsen dataset: it provides detailed individual volume and price data across hundreds of locations and thousands of products; it contains proprietary private data that are not normally made available to researchers; and it collects data at a weekly frequency, rather than a monthly one, thereby allowing us to

compare and contrast with official price data from the ONS, and test the impact of data collection frequencies on the observed behaviour of prices. Further detail on the Nielsen data is available in Ellis (2009a).

After initial conversations to set out the nature and potential scope of the research, Nielsen agreed to make available a large dataset of individual product-level data, based on their collections from the largest UK retailers. This included Tesco, Asda, Sainsbury's, Morrison's, Waitrose and the now-defunct Somerfield.

3.4 *Data access arrangements*

For both the ONS and Nielsen, controlling access to the underlying microeconomic data was a key concern. In the case of the ONS, it is possible to identify individual companies from the detailed pricing and IDBR data that are collected during the formation of the CPI and PPI. Because of the confidentiality issues relating to information collected about individual people or firms, it is therefore not possible to make this type of data widely available. In the case of Nielsen, the data are central to its operating model of providing bespoke analysis to producers and retailers.

This meant that, in both cases, strict data access arrangements were imposed. The ONS recognises that its data are a very valuable resource, and hence has developed a secure facility for genuine academic researchers to work with the data. The Virtual Microdata Laboratory (VML) was launched in January 2004 with the explicit aim of allowing researchers access to data while also maintaining confidentiality and security. Initially only business survey data were available, but the number of data sets stored in the VML has expanded considerably over time. The micro data that underlie the consumer and producer price indices described in this context statement were first made accessible via the VML in late 2007.

The VML is located on ONS premises, and no data or results are allowed to be taken into or out of the laboratory directly by researchers. There is no access to the outside world via email or the internet for those working in the laboratory and all outputs have to be cleared by ONS staff before they are released to researchers to ensure they contain no confidential

information. Access is only granted for a valid statistical purpose and all researchers are given training and vetted. Since its inception, the VML has been used by hundreds of researchers from a variety of backgrounds: Ritchie (2008) provides further details on the VML. The use of ONS micro data to inform the analysis presented in this submission is the first time any researchers have used the VML to conduct detailed analysis of individual prices in the United Kingdom.

Arrangements for accessing data at Nielsen were very similar to those for accessing official ONS data, due to Nielsen's data also being highly confidential and market sensitive. In order to access the data, I had to physically travel to Nielsen's Oxford office on a number of different occasions. There, I was kindly provided with a basic computer with very few applications other than STATA. As with the VML, I was unable to access the internet or email, and all results from my analysis were stored locally on Nielsen's computer. After reviewing my output files, Nielsen staff then released those files to me, and I was able to write up my results and analysis as normal.

In all instances, the final research papers resulting from the analysis were circulated to the ONS and Nielsen prior to publication.

3.5 *Coverage of the data samples*

Having set out the background to the different data sources and the specific access arrangements, this section sets out the characteristics of the individual microeconomic datasets. These are a key component of the original contribution from the public works.

3.5.1 *The PPI dataset*

In examining official sources of microeconomic price data, both the PPI and CPI were considered. In the case of the PPI, the data set includes around 430,000 individual producer price quotes, covering 18,000 products produced by 9,000 firms. Data are monthly, and cover the period between 2003 and 2007. Imputed data were excluded in order to focus on actual price quotes; a very small number of ‘zero’ price quotes are excluded as well.

The PPI data panel is not balanced: new firms (and products) enter and existing firms exit frequently. Around 10% of items are present in the data set for all 48 months, and some other items rotate in and out of the sample. On average, an item is present for around two years. Unless otherwise stated, the results that follow are presented on a weighted basis, where these weights were supplied by the ONS.

All results presented herein take the underlying PPI data as accurate. In practice, PPI micro data will be subject to both sampling and non-sampling error, as described in ONS (2007a). One particular issue could be a specific form of non-sampling error: the underlying PPI survey asks respondents about their ‘normal transaction price’, which should be the price

manufacturers achieve in a significant proportion of UK sales and representative of current output. If survey respondents find it difficult to report 'like with like' prices each month, this could introduce errors into the raw micro data. However, given the immense difficulties in identifying and compensating for these types of errors, the underlying microeconomic price data are taken as given.

3.5.2 The CPI dataset

In the CPI microeconomic data, the analysis used locally collected price quotes, which reflect the price of a particular item in a particular shop in a given month. As discussed earlier, the ONS examines the price data carefully ahead of aggregation. As such, there were a small percentage of prices in the micro data – which tended to be outliers or 'zero' price quotes – that were not used in the construction of the headline CPI data, and are also excluded in the analysis that follows. As with the producer price data, observations were also dropped where there was no price quote for corresponding item in the previous month, since it was not possible to identify whether the price had changed. This is arguably akin to left-censoring the data, although only by one observation for each item. Our cleaned sample represents approximately 85% of the full set of locally collected CPI data.

The CPI data set used in the public works covered the period from 1996 to 2006, and included a total of just over 11 million individual price quotes. Each of the item-locations is tracked individually in the CPI data, and in total there are just under 600,000 different items in the data set. As with the producer price data, the panel is not balanced: new products enter and existing products exit. The sample is updated annually, in February, although there is still some rotation in the intervening period because the prices of specific items may

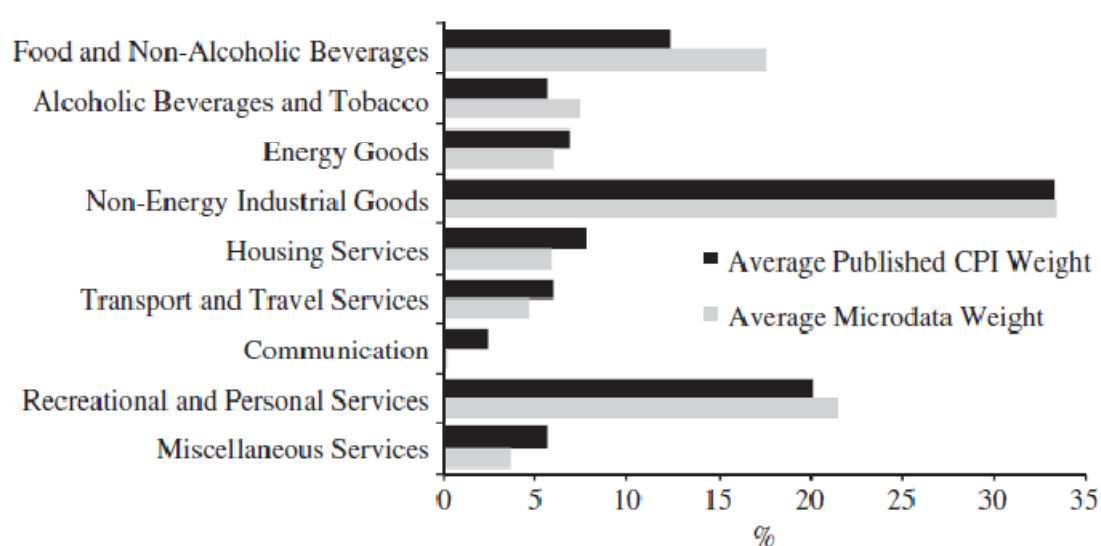
no longer be available. There is also significant attrition in the data set as individual items are modified, dropped or change location: only 96 items are in the data every month across the whole 11 year sample. In all, around 700 items are in the data for more than 10 years and 17,000 are present for at least 5 years. The mean number of months in the sample for an item is 19; the median is 13. Unless otherwise stated, the results presented herein are on a weighted basis. The weights represent the share of each item in the locally collected CPI in each month.⁶ As with producer prices, all the following results ignore potential measurement error in the collection of the underlying CPI micro data, given the difficulties in identifying and correcting these errors. Implicitly, the analysis assumes that the data collection and checking processes described earlier minimise these potential measurement errors; any that remain would imply greater uncertainty around the results that follow, but not necessarily bias in the results.

Given that the sample covers only locally collected CPI data, it is not fully representative of the CPI as a whole. Some prices are more likely to be collected centrally than locally – for instance, by accessing common internet-based prices rather than physically visiting shops in different locations. This means that the micro data sample will have a higher weight for those items that are collected locally than in the published CPI. Figure 3.2 shows the average weight within the micro data sample for each broad component of CPI, compared with the weights within the published CPI data. Some components such as food and non-alcoholic beverages have a higher weight in the micro data than in published CPI, because these prices are more likely to be collected locally than centrally. The only broad

⁶ The ONS collects larger samples of prices for some types of products where they believe it is necessary to produce a reliable estimate of the average price. Weighting the results avoids biasing them towards these types of products. The weights are based on consumers' spending, and they represent the individual weight of each particular item in the aggregate CPI in each month.

component for which there is very little micro data is communication, although education prices (within miscellaneous services) are also missing. Together, these categories account for around 3% of the published CPI over the micro data sample. In general, however, the differences between the micro data and the published weights by component are relatively small.

Figure 3.2: Broad category weights by CPI component



The CPI micro data could also be unrepresentative if the locally collected prices within each component are not representative of the centrally collected items. In many cases, it may be reasonable to assume that they are representative. But close inspection of the data reveals one particular instance where this may not be true: the prices of energy goods. The micro data sample of energy goods prices is dominated by petrol and diesel prices. The other major group of energy goods in CPI are gas and electricity utility prices, which are centrally collected. It is likely that petrol prices behave differently (e.g. change more frequently)

compared with utility prices. As such, the energy category in the micro data may not be fully representative of the CPI energy category.

3.5.3 The Nielsen dataset

The supermarket analysis was based on a bespoke data set created from Nielsen's database. It covered around 240 different supermarkets located throughout Great Britain, covering the largest retailers. In total, just over 280 distinct products were included in the dataset; however not all stores stock all products, and some products appear intermittently. The individual products were chosen with consideration to brand importance (see Nielsen, 2007), data availability, and to try to get a broad range of different types of goods.

The dataset covered three years of sales on a weekly frequency, covering selling prices and the quantity sold. The data set started in the week of 19 February 2005 and ended in the week of 9 February 2008. In all, there are just under 5½ million individual price observations, or roughly 35,000 different price observations each week; total sales in the dataset accounted for a little under 5% of annual household expenditure. The price observations were 'average' prices for each week: this means that temporary changes in prices, such as selling damaged goods more cheaply, will appear in the data. Averaging could also have other implications: for example, multi-buys will have an impact on the data, and a price cut may appear in two separate observations if it happens mid-week.

The products were grouped by Nielsen into ten different categories: Alcohol; Bakery; Confectionary; Dairy; Fresh (e.g. fruit and vegetables); Frozen; Grocery; Household; Personal (e.g. health care); and Soft Drinks. Sales values for each category, as a proportion

of total sales in the data set, are shown in Table 3.1: the Fresh category clearly dominates. In the results that follow, this high weight must be borne in mind. Unless otherwise stated, the results that follow are weighted by sales values for individual items; consequently, the analysis reports alternative results when the 'Fresh' category is excluded.

Table 3.1: Share of supermarket sales by product category

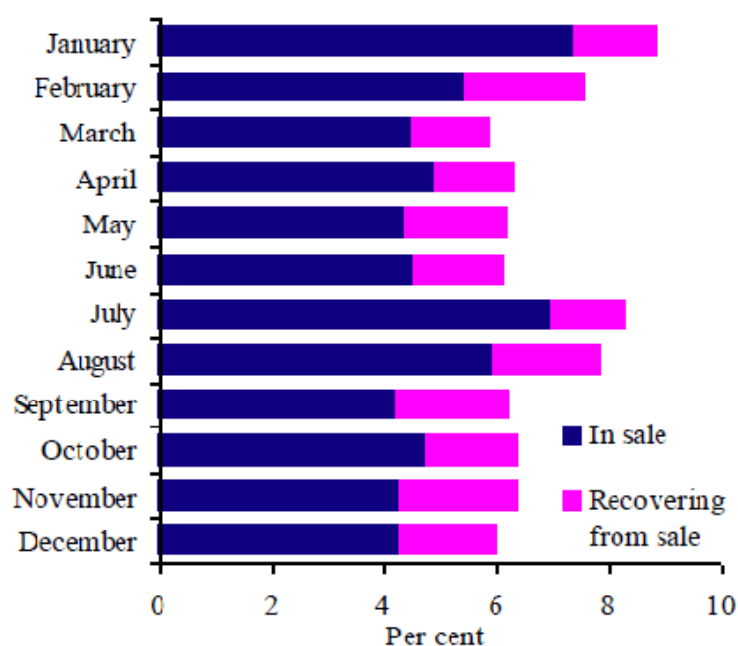
Category	Frequency		Sales	
	Number	% of total	£ million	% of total
Alcohol	319195	5.6	6449	5.9
Bakery	161087	2.8	1624	1.5
Confectionary	544268	9.6	2318	2
Dairy	614746	10.8	12778	11.7
Fresh	1030831	18.1	61890	56.7
Frozen	255294	4.5	1986	1.8
Grocery	1234536	21.7	10323	9.5
Household	408352	7.2	3430	3.1
Personal	492449	8.7	2460	2.3
Soft Drinks	621778	10.9	6033	5.5
<i>Total</i>	<i>5682536</i>	<i>100</i>	<i>109110</i>	<i>100</i>

3.6 *Identifying temporary price changes*

One important issue before conducting the analysis of the underlying data is to consider the role of temporary price changes, which may reflect discounts offered during ‘sales’ periods or potentially variations in product quality. Previous work such as Kehoe and Midrigan (2007) and Eichenbaum *et al* (2008) has noted the important role of temporary discounts or ‘sales’ in analyses of high-frequency prices such as scanner data. The same may also be true of other measures of consumer prices.

In the case of CPI data, ONS price collectors helpfully mark whether a particular price in any given month is a ‘sale’ price – strictly, a temporarily discounted price – or not. This means it is also possible to identify prices that are recovering from a sale or temporary promotion in the previous month: Bunn and Ellis (2011) provide more detail here. On average across the sample, roughly 5% of all price quotes are items that are marked as sale prices, and 2% are items recovering from a sale. Figure 3.3 illustrates that January is (unsurprisingly) the most popular month for sales, which are overwhelmingly observed for goods prices (and only infrequently observed for services prices).

Figure 3.3: Percentage of CPI price quotes that are sales by calendar month



Regrettably, no reliable indicator of ‘sale’ periods was available in the PPI or Nielsen data.

As such, the analysis that follows considers three options for adjusting the data to take account of these temporary price moves. The first is the so-called ‘reference price’ suggested by Eichenbaum *et al* (2008). The ‘reference price’ is simply the modal price within a given quarter; the choice of a quarterly reference period seems arbitrary. If sales are an important driver of price volatility, using reference prices will clearly wash a significant degree of variability out of the underlying price data – in particular, reference prices will not change at all within the three-month reference window.

The second option is the notion of a ‘regular price’, as defined by Kehoe and Midrigan (2007). This classifies price reductions as sales if they are reversed sufficiently quickly, within some defined period. The ‘regular price’ is generated from the observed price series, smoothing through these identified short-term price changes. However, I also developed an

original third approach for dealing with temporary price changes, which eliminated ‘price reversals’. These two approaches are set out in the following sub-sections.

3.6.1 *The regular price algorithm*

Using weekly price data, Kehoe and Midrigan (2007) construct the regular price series, P_t^R , based on the original price series, P_t , as follows:

Step 1: return to above or to the same level

Whenever the actual price series falls, i.e. $P_t < P_{t-1}$, check whether the actual price rises above its current (new) level over the next five weeks: i.e., check if $P_{t+j} \geq P_t$ for $j \leq 5$. If it does, then let J be the minimum j for which this condition is satisfied (if at all); in other words, the first time the observed price rises back to or above its past level, P_{t-1} , is defined as period J . If the condition is not satisfied, no modifications are made to the data. If it is, then to construct the regular price series observed prices prior to period J are overwritten: we replace $P_t, P_{t+1}, \dots, P_{t+J-1}$ with P_{t-1} to construct P_t^R .

Step 2: return below the original level

For each price cut, defined as $P_t < P_{t-1}$, check if $P_{t+j} \geq P_t$ for $j \leq 5$. Let J be the minimum j for which this condition is satisfied, as before. Replace $P_t, P_{t+1}, \dots, P_{t+J-1}$ with P_{t-1} as before to construct P_t^R . Repeat this second procedure five times in order to filter out sales periods associated with price changes following the original price cut.

3.6.2 Price reversals: an original approach for eliminating temporary price changes

Both the 'regular price' and 'reference price' options are based on one critical assumption: the time period over which temporary deviations are observed and ignored. Hence, both concepts are 'time-dependent' in the sense that they will be determined by this (subjective) period length. However, true sales patterns could be heterogeneous between and within product categories, which could make such a broad-brush time-dependent approach inappropriate.

In light of this, the third option for removing temporary price deviations is free from this concern. A 'price reversal' can be defined as occurring when prices move either up or down, before exactly reversing at some later (unbounded) point in time. This could potentially lead to long periods between price falls and subsequent reversals. However, if the average sales duration of two weeks found by Kehoe and Midrigan (2007) holds in the UK supermarket data, then the behaviour of price changes using either 'regular prices' or stripping out 'price reversals' should be similar. In addition, stripping out price reversals also overlaps with the concept of a 'reference price'. If most deviations from some 'normal' price are temporary sales that are reversed, a clearer picture of that 'normal price' should emerge once price reversals are stripped out. If this normal price is the mode within a three-month window, it will match the reference price. As such, the different methodologies for accounting for 'temporary' price changes can act as a cross-check on one another.

This new approach to identifying temporary price changes was an original contribution of Ellis (2009b), and was used to examine the impact of temporary prices changes on empirical estimates of price duration.

Chapter 4 Analysis of microeconomic prices and implications for policymakers

4.1 *Introduction*

Having examined the existing economic literature, there was a clear gap relating to the importance of directly examining how UK prices behave at the individual level, rather than relying on inferences from aggregate price indices. However, doing so is not straightforward; Chapter 3 set out the detailed access arrangements and characteristics of the three unique and original UK datasets that formed the underlying material for the research presented in several of the public works.

Having managed to uncover and access these different datasets, this Chapter provides a summary of key results from the analysis in the submitted public works. These include the two *Economic Journal* articles (Bunn and Ellis, 2012a and 2012b) and the more detailed supermarket pricing paper (Ellis, 2009a). These results are then compared and contrasted against the implications of standard theoretical pricing frameworks, to see if they can match the actual behaviour of prices.

The results are also important for monetary policy makers; as detailed in previous research, the different behaviour of individual prices within and across sectors can have marked consequences for the optimal path of monetary policy. This issue is considered in another of the submitted public works (Ellis, 2009b), which focuses in particular on the optimal choice of the nominal anchor, both in terms of its coverage and level. In addition, standard monetary policy models may rely on assumptions that are not borne out by the data; as

such, this Chapter also draws upon the final public work (Mumtaz *et al*, 2009), which details a new modelling framework that allows UK policymakers to capture both macroeconomic tractability and microeconomic heterogeneity. This paper builds on previous US work in this field, but also proposes a new and innovative strategy for identifying the model, linked with recent developments in vector autoregression (VAR) work.

4.2 *Microeconomic evidence on the behaviour of UK prices*

Having uncovered and negotiated access to the microeconomic data detailed in the previous Chapter, it was now possible to examine how UK prices actually behave. This section provides a summary of results from Bunn and Ellis (2012a and 2012) and Ellis (2009a), which describe new empirical evidence about how individual prices actually behave in the UK economy. These papers should be referred to for further details.

4.2.1 *The frequency of price changes*

A first question concerned the frequency of price changes: Table 4.1 presents headline results. On average, 19% of official consumer prices change each month, implying an average duration between price changes of approximately five months. Around 7% of the price quotes in the CPI data are identified as either being temporarily discounted sale prices or prices recovering from a sale in the previous month, as described in the previous section. Excluding these observations relating to sales, the proportion of consumer prices changing each month falls to 15%.

Table 4.1: How often do prices change?

Microeconomic price data	Sample	Percentage of prices changing	Implied duration between price changes
Monthly CPI microdata	1996-2006	19% a month	5.3 months
CPI goods	1996-2006	24% a month	4.2 months
CPI services	1996-2006	9% a month	11.1 months
All items excluding temporary discounts	1996-2006	15% a month	6.7 months
Monthly PPI microdata	2003-2007	26% a month	3.8 months
Weekly supermarket data	2005-2008	60% a week	1.7 weeks
Excluding Fresh products	2005-2008	40% a week	2.5 weeks
Excluding Fresh products and price reversals	2005-2008	27% a week	3.7 weeks

Consistent with previous research set out in Chapter 2, these aggregate figures are likely to mask considerable heterogeneity among different product groupings. We might expect sectors or products that are more dependent on raw materials to exhibit more frequent price changes, if the prices of those underlying materials changes frequently. In contrast, sectors that are more dependent on labour inputs may exhibit price changes that are more closely correlated with changes in wages and productivity. More competitive sectors, in terms of selling practices, may potentially also exhibit more frequent price changes than more monopolistic markets.

The disaggregated data support this supposition. Consumer goods prices change more often than the prices of services: an average of 24% of goods prices change each month, compared with only 9% for services. The results suggest that UK consumer prices change slightly more often than in the euro area, where 15% of prices were found to change each month (Dhyne *et al*, 2006). But UK consumer prices appear to change less often than in the

United States, where around 26% of prices are estimated to change each month (Bils and Klenow, 2004). One point of note is that these cross-country comparisons are all made using results that include discounted 'sale' prices.

Overall, the UK producer price results are similar to the results for UK CPI goods prices. The PPI only covers goods prices, so comparison with the CPI goods category is more natural than with the whole of the CPI (which also includes services). On average, 26% of producer prices change each month, compared with 24% of consumer goods prices. The finding that producers' goods prices change with similar frequency to prices charged for retail goods suggests that few pricing frictions exist between the production and retail sectors in the United Kingdom.

The finding that roughly a quarter of UK producer prices change each month is also consistent with evidence from the United States, where a similar proportion of producer price changes was observed (Nakamura and Steinsson, 2008). However, it implies that UK producer prices may be a little more flexible than in the euro area, where only 21% of producer prices are estimated to change each month (Vermeulen *et al*, 2007).

Weekly supermarket prices appear to change much more frequently than is implied from analysing the prices used in the construction of the CPI and PPI indices. The data suggest that, excluding fresh products, around 40% of prices change each week, implying that the average duration of prices is around two and a half weeks. As noted earlier, the sample was heavily weighted to fresh products (57% of the sample), where prices change frequently; this is consistent with the hypothesis that products that are closely linked to raw materials

may exhibit frequent price changes. However, such a high weight on fresh products is not representative of broader spending patterns; as such, excluding these products may give a better read on underlying price flexibility. The supermarket data exhibit a lower price duration than the CPI retail goods data, but the data frequencies are obviously different.

To check this result, I also examined the frequency of supermarket price changes based on the 'regular price' algorithm described in the previous Chapter, along with analogous results when price reversals are excluded. These results are shown in Table 4.2; the two approaches yield broadly similar results once Fresh products are excluded.

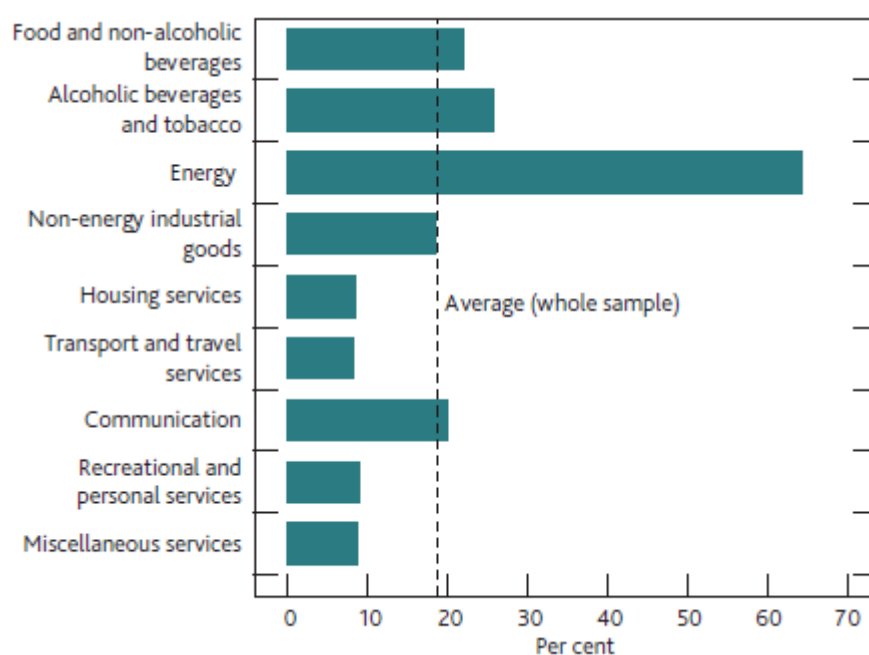
Table 4.2: Frequency of supermarket price changes

Prices changing per week	%
Total	60.0
excluding price reversals	45.3
based on 'regular' prices	37.3
Excluding Fresh products	40.4
excluding price reversals	27.0
based on 'regular' prices	24.3

There are a number of reasons why supermarket prices change more frequently than consumer prices as a whole. First, the weekly supermarket data are picking up large numbers of temporary promotions that are not captured in the monthly CPI data. Excluding price reversals, as described in the previous section, the share of prices changing each week (excluding fresh products) falls to 27%. Second, the supermarket sample is predominantly food items, and food products within the CPI change price slightly more frequently than the average for all products (Figure 4.1). Third, the CPI data cover prices from a much wider

range of shops than just large supermarkets and price-setting behaviour may not be the same among all types of retailers. Nevertheless, the relatively high levels of flexibility observed in the weekly scanner data could also reflect the fact that only one observation for each price is available each month in the ONS micro data. This can also be investigated using the higher-frequency scanner data, adding further value to the analysis that is not possible using the CPI micro data alone; the higher-frequency data allow for more detailed investigation.

Figure 4.1: Percentage of CPI prices that change each month by component



In particular, the differing estimates of price flexibility suggest that the frequency of data collection could be having an impact on empirical observations of price flexibility. By construction, the most frequently CPI or PPI prices can change is once a month. In contrast, Nielsen scanner prices could potentially change every week. By examining how the estimated price duration changes when high-frequency scanner data are aggregated into

monthly or quarterly observations, we can examine how much of an influence the frequency of data collection can have on observed price durations.

In order to examine this, I calculated monthly and quarterly reference prices in line with Eichenbaum *et al* (2008) using the underlying weekly scanner data. When calculating quarterly reference prices, one issue was the existence of multiple modes within three-month periods. To address this, reference prices were set as the highest mode within the quarter, on the basis that most temporary promotions are likely to exhibit lower prices than normal. Table 4.3 presents results from the reference price series: even excluding the ‘Fresh’ category, 50% of quarterly reference prices change each quarter, implying an average duration of six months, longer than the observed duration of goods prices from the CPI data.

Table 4.3: Frequency of price changes in supermarket reference prices

Reference prices changing per period	%
Quarterly reference prices	
Total	68.7
Excluding Fresh products	50.3
Monthly reference prices	
Total	64.0
Excluding Fresh products	44.0

If reference prices are calculated over a one-month window (rather than over three months), the results change. Now, 64% of those reference prices changed each month (44% excluding Fresh), implying an average price duration of just under (over) two months. These results clearly demonstrate how critical the length of the reference window is: picking too

long a window could upwardly bias the implied duration of prices. It also demonstrates that by focusing on low-frequency data, be it monthly or quarterly, we can miss much of the higher-frequency variation that may actually be present in prices.

4.2.2 Price changes across product categories

As noted above, consumer goods prices change more often than services prices. But there are also differences in how often prices change within these categories (Figure 4.1). In particular, the prices of energy items in the CPI – dominated by petrol – change the most frequently. The evidence of heterogeneity is also clear in the supermarket data (Figure 4.2) and in the producer price data (Figure 4.3). In the supermarket data the prices of Fresh products (which also have the largest weight) change the most often, and in the producer price data, energy products change price the most frequently (as in the consumer price data).

Figure 4.2: Percentage of weekly changes in UK supermarket prices

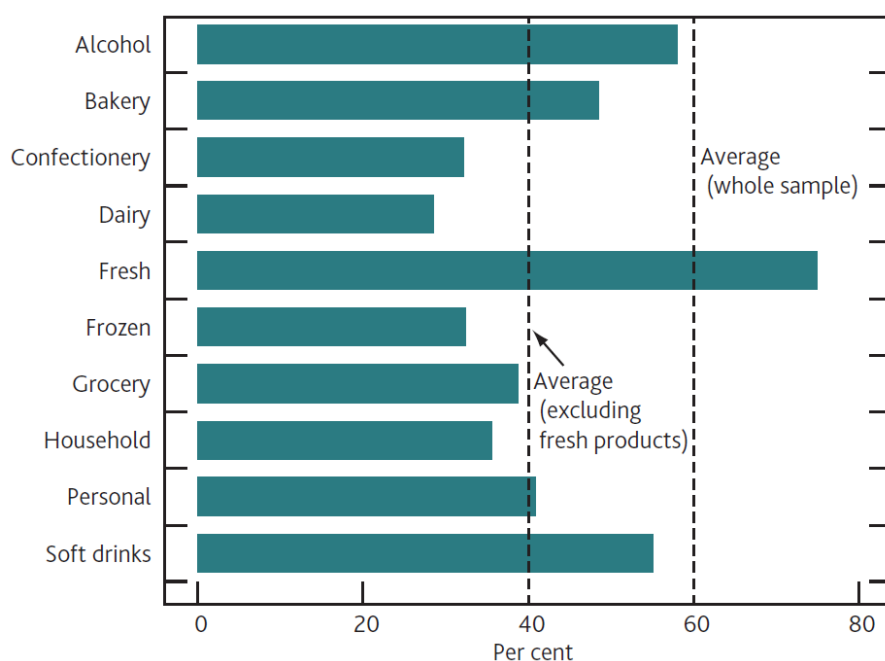
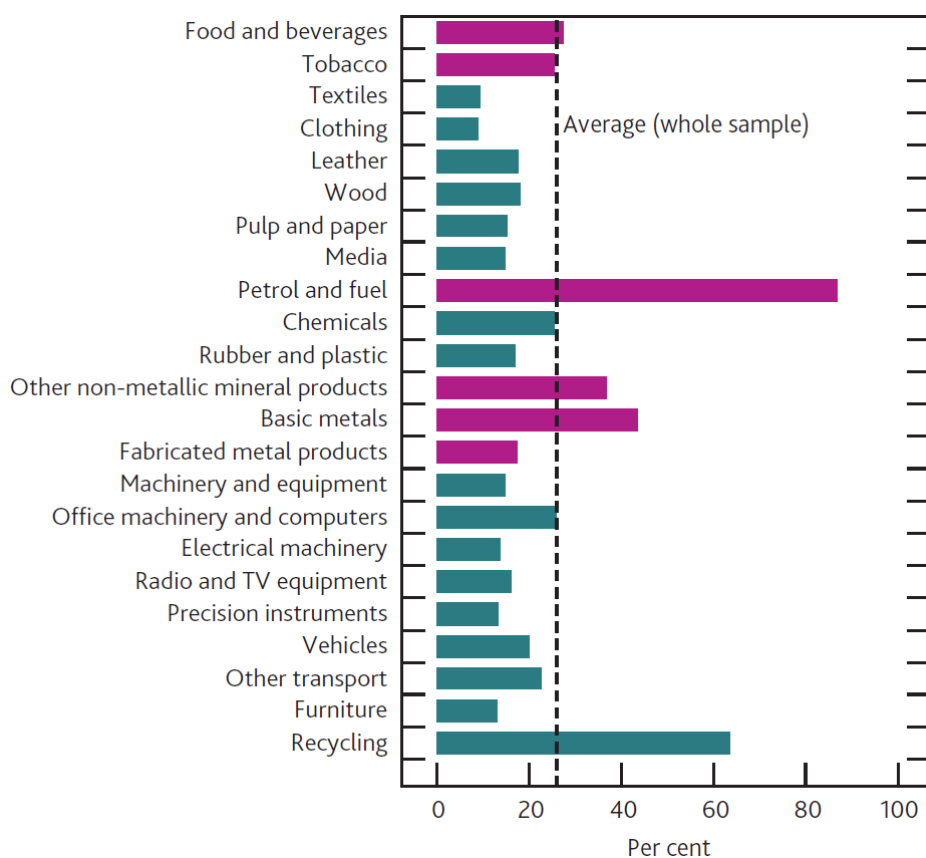


Figure 4.3: Percentage of monthly producer price changes



For producer prices, those sectors that use a high proportion of primary inputs — agriculture, metals and energy — tend to exhibit higher frequencies of price change than average (the magenta bars in Figure 4.3). The prices of these relatively commoditised inputs can change on a daily basis, and this appears to feed through to companies' output prices. The only sector with a very high proportion of prices changing each month that uses less primary inputs is recycling. Although the inputs to this industry come from across the economy, the output is a type of commodity and therefore it is likely that output prices charged will be closely linked to prices in commodity markets, which can exhibit substantial variation.

4.2.3 Price changes over time and hazard functions

In examining the behaviour of prices, it is also useful to consider how the likelihood of prices changing varies over time. This can give some idea of how sample-specific the results are, as well as providing a test of time-dependent pricing models. In its simplest form, a strict time-dependent Calvo (1983) pricing model implies that the probability of a price change is the same in each period. There are two ways to explore whether the probability of price changes varies over time: first, to look at the frequency of price changes in different periods; and second, to draw so-called 'hazard functions' which plot the probability of a price change against the time elapsed since the previous change.

It is well known that there is seasonal variation in prices, and this is evident in the microeconomic pricing data: for example, more consumer prices change in January than in any other month of the year as firms reduce prices as part of the January sales. Excluding all

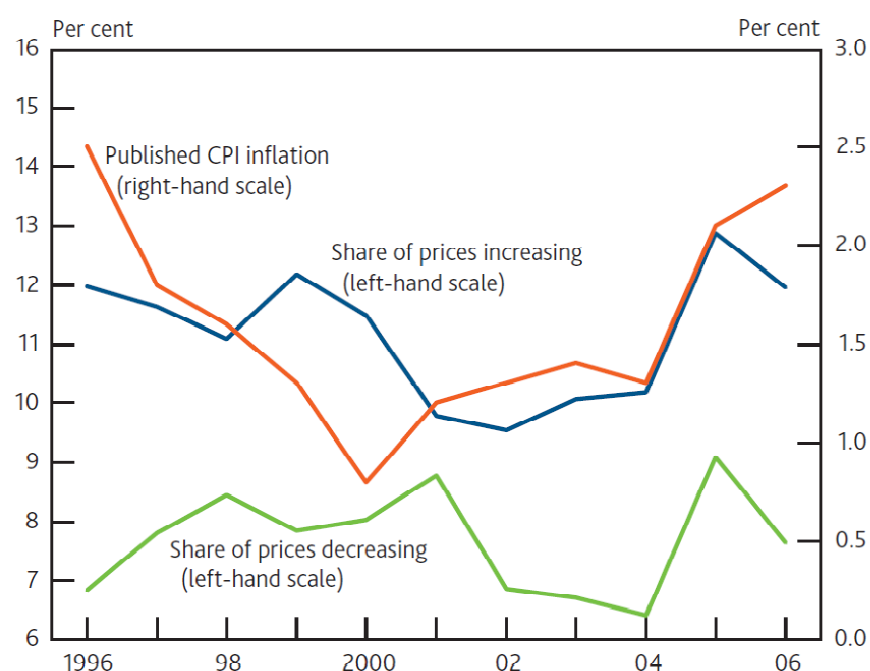
sale prices, consumer prices are most likely to change in April. That could reflect changes in duties, consistent with price regulation and broader fiscal policy influencing the behaviour of individual consumer prices as discussed in Section 3.3. These considerations must be borne in mind when interpreting results from the micro data, as regulated prices may change less frequently than unregulated prices, and changes in duties and VAT will affect selling prices even when underlying basic prices (i.e. prices excluding duties and VAT) are unchanged.

One interesting contrast here is with producer prices, which are collected on a 'basic price' basis. As such, producer price quotes should exclude VAT and duties, and hence be unaffected by changes in these taxes. However, the PPI micro data also indicate that producer prices are most likely to change in January and April, consistent with consumer prices. This could be consistent with fiscal decisions having less impact on the timing and frequency of price changes than first thought; or, potentially, it could reflect firms synchronising changes in their (basic) selling prices to coincide with changes in duties and other taxes. Both consumer and producer prices appear to change least often in November and December.

The average share of consumer prices changing each month varies between 16% and 22% in different years of the sample. For producer prices, the annual average proportion of prices changing each month ranges between 24% and 28%. In the CPI micro data, which spans the longest time period of the three data sets (1996 to 2006), there is some evidence of a correlation between the average share of prices increasing each month and the aggregate inflation rate that these individual price quotes underlie (Figure 4.4). However, there is no

sign of a relationship between inflation and the share of prices decreasing. A similar relationship appears to hold for producer prices, albeit over a shorter time horizon. The share of supermarket prices changing each week also varies over time. This widespread evidence of variation in the frequency of price changes over time is not consistent with the predictions of a simple time-dependent pricing model.

Figure 4.4: Shares of CPI price changes and aggregate inflation



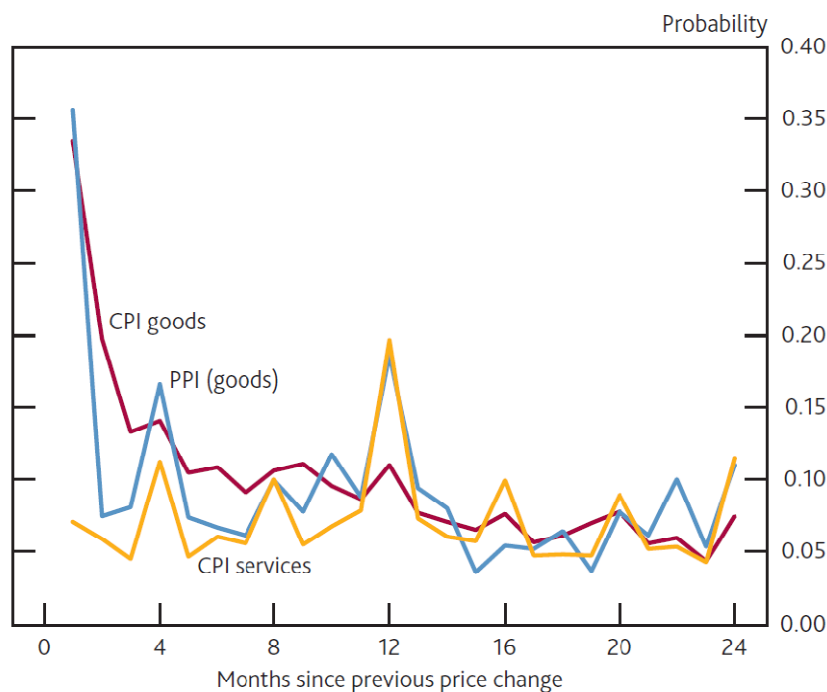
Thus far, the analysis has concentrated on the average frequencies of prices changing, which can be interpreted as unconditional probabilities of price changes. The conditional probability of a price change is also important: in this context, the relevant conditional probability is the probability of a price change occurring given the time that has elapsed since the previous price change. This is measured by estimating hazard functions. The hazard function, $h(t)$, measures the probability that a price will change in period t given that it has not changed in previous periods (equation (3)). It is calculated as the share of firms

adjusting their price in period t , $f(t)$, over the share of firms who have not changed their price in previous periods, $s(t)$, which is also known as the survivor function:

$$h(t) = \frac{f(t)}{s(t)} \quad (3)$$

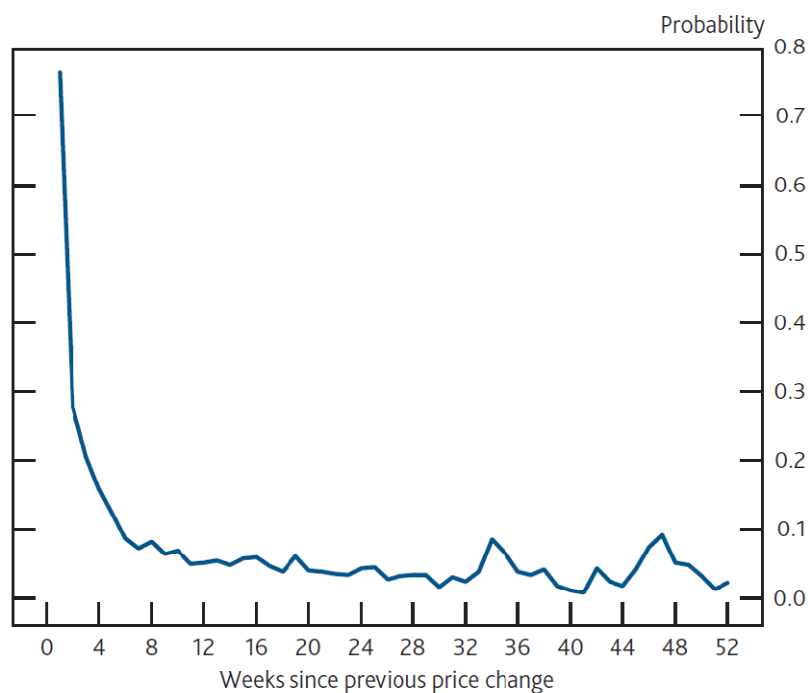
In estimating hazard functions, only items that have at least one price change were included in the analysis, due to the need to filter out left censored observations (we need to be certain how many months have elapsed since the previous price change). Each item is used only once in the hazard function estimation – that is, the function examines the time between the first and the second price change (if there is one).

Figure 4.5: Consumer and producer price hazard functions



Consumer goods prices are most likely to change in the month after they previously changed (Figure 4.5), and the probability of a price change falls as more time passes since the price last changed. The spike at one month may in part be picking up temporary price promotions. The hazard function for consumer services prices looks quite different: it is more horizontal with a notable spike at twelve months, which is suggestive of annual price reviews. The hazard function for producer goods prices has a large spike at one month and slopes downwards, broadly matching the consumer goods price data, although the one major difference is that it also has a spike at twelve months. This could well represent the annual price reviews noted by Hall *et al* (2000) in their survey of firms.

Figure 4.6: Supermarket price hazard function



In the supermarket price data, the probability of a price changing is very high if that price also changed in the previous week (Figure 4.6). After the first week, the probability of a price change then declines. The shape of the supermarket price hazard function is broadly

similar to that for the CPI goods data, except that prices change on a much more frequent basis, consistent with earlier results.

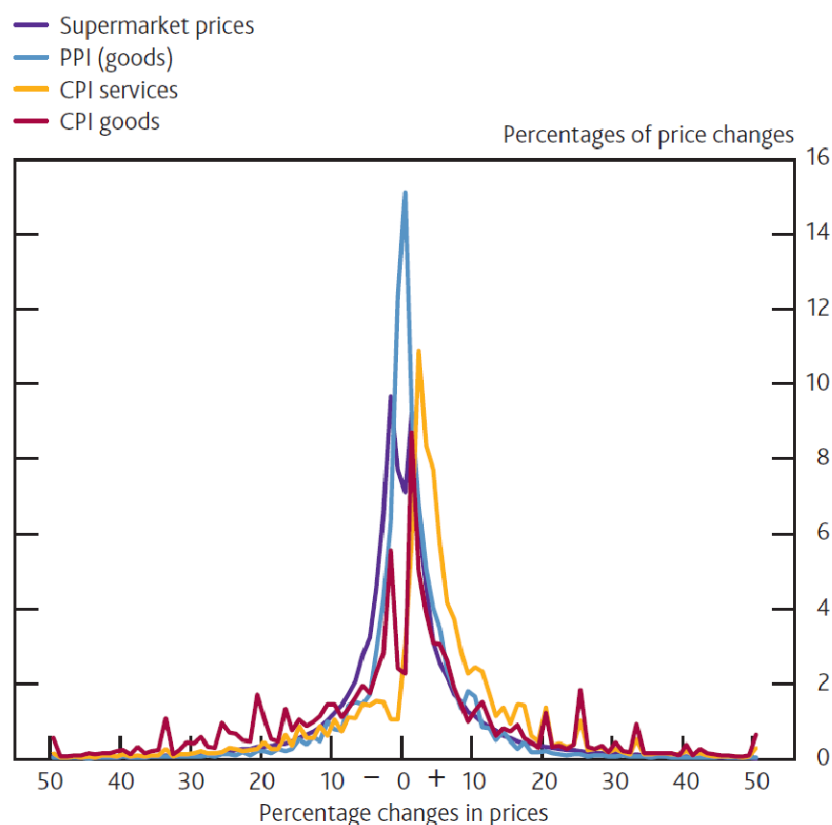
A simple time-dependent Calvo pricing model would suggest a broadly flat hazard function, implying that the probability of a price change depends only on when the price last changed. The downward-sloping hazard functions found in the microeconomic data are inconsistent with that modelling approach.

4.2.4 The magnitude of price changes

Analysing the size of price changes provides further information about how individual prices behave. It may also be useful to help determine whether firms face costs in adjusting their prices, as is assumed in some state-dependent pricing theories set out in Chapter 2. The existence of relatively few small price changes might suggest that fixed costs of price adjustment — or menu costs — are important. By contrast, if firms face disutilities from making large price changes, then that would suggest that the majority of price changes should be small.

Across all three data sets the median price change is an increase of between 0% and 2%. For each data set, the distribution of the size of price changes around the central estimates is wide with considerable variation in the magnitude of observed price changes (Figure 4.7). But there are also a significant number of price changes that are relatively small and close to zero, and the distributions fail the usual normality tests.

Figure 4.7: Distribution of the size of changes in prices



The proportion of small price changes is particularly high for producer prices. There tend to be more increases and fewer decreases in consumer services prices than in goods prices, although that may reflect higher rates of services price inflation compared with goods price inflation over the sample periods.

The distribution of the size of supermarket price changes looks broadly similar to the distribution of the size of consumer goods price changes. However, there is a higher proportion of smaller price falls in the supermarket data. This might suggest that temporary promotions — where price changes tend to be relatively large — cannot fully explain why weekly supermarket prices appear to change so much more frequently than CPI goods prices. It could also reflect the supermarket data recording average prices where short-term

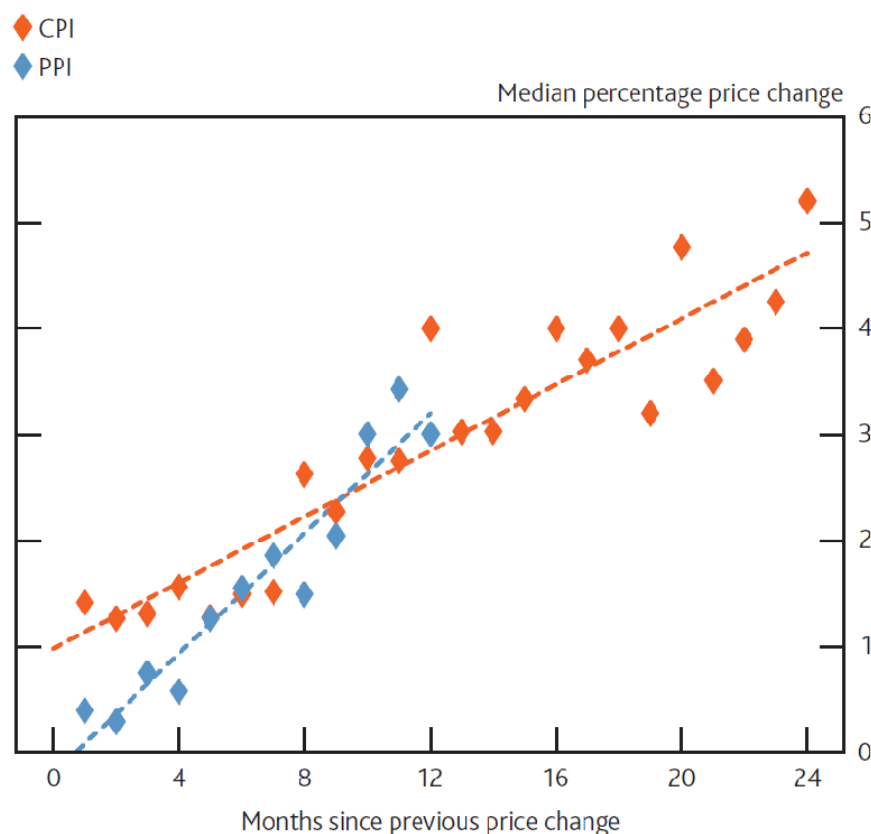
price reductions, for example to sell off stock approaching its sell-by date, might explain some of the small price changes. This is particularly relevant for Fresh products, which make up a significant proportion of the sample.

State-dependent pricing models typically assume that firms face a small fixed cost to adjust their prices, or face disutilities associated with making large price changes such as losing customers and market share. The large numbers of relatively small price changes that occur in all data sets imply that small fixed costs of price adjustment may not be important for many firms. At the same time, the large price changes that are present in the data are not consistent with firms being dissuaded from making large price changes. As such, this evidence suggests that these standard state-dependent pricing models may not explain price-setting behaviour for the majority of products and firms. The sizeable proportion of negative price changes across all three microeconomic datasets also suggests that downward nominal rigidities are not a prevalent feature of UK product markets.

4.2.5 Links between the frequency and magnitude of price changes

Apart from examining the frequency and magnitude of price changes separately, we can also consider linkages between the two. If prices can be (re)set in each period, there is no reason to expect price changes to be larger if more time has passed since the price last changed. But if some constraint exists that only allows or incentivises firms to set prices at infrequent intervals, there is more scope for a firm's actual price to differ from its optimal price as the duration since the previous price change increases. Examples of such constraints might include contracts of fixed length or costs of price adjustment.

Figure 4.8: Size of price changes and duration since the previous change



Consumer prices that change more frequently tend to do so by less (Figure 4.8). This relationship is particularly strong for CPI services prices. This relationship between the frequency and magnitude of price changes also holds in the producer price data, at least for periods of up to one year. Beyond one year the producer price sample size is much smaller, which makes it more difficult to test this hypothesis. However, in the supermarket price data there is no strong link between the frequency and magnitude of price changes. This may be related to prices changing much more frequently in the weekly supermarket data, which means price durations tend to be short in this data.

4.3 *Implications for pricing theories and monetary policy*

The analysis of microeconomic price data reveals a number of new and interesting findings that are critical to understand the impact and role of UK monetary policy. The implications of these findings are discussed in the submitted public works (Bunn and Ellis, 2012a and 2012b, and Ellis, 2009a) and summarised here. First, prices do not adjust completely continuously in the United Kingdom – even using the weekly supermarket data, not every price changes every week or month. This means that, even if firms do review prices more frequently than price changes are observed, as suggested by Hall *et al* (2000), there is some degree of nominal rigidity in UK product markets. This is consistent with monetary policy being able to influence the short- to medium-term dynamics of the real economy.

The second key result is the marked degree of heterogeneity that exists in UK price setting, both between industries and within sectoral groupings. Prices in the UK economy do not all behave in the same way: they change with different frequencies, and magnitudes, and at different times across different sectors.

The third key result relates to the theoretical pricing models described in Chapter 2. The marked heterogeneity in the behaviour of individual prices implies that no single pricing theory is consistent with the observed empirical analysis. The strict Calvo (1983) time-dependent price-setting model is not consistent with the variation in the share of prices that change in different years, or the downward-sloping hazard functions that are observed across most sectors. At the same time, the state-dependent menu cost models also appear to fall short: if menu costs were a key driver of nominal rigidities, we would expect to see

very few price changes within a small range, such as between -2% and +2%, as the benefits of changing price by such a small amount would be outweighed by these menu costs. In fact, the microeconomic evidence shows that a large proportion of all price changes are within this range across all three datasets, which is not consistent with the menu cost pricing model.

Similarly, the implications of the quadratic adjustment cost model proposed by Rotemberg (1982) are not borne out by the data. In that approach, firms adjust prices continuously but by small amounts; yet in the microeconomic price data, we observe both non-continuous price adjustment and a number of large price changes that are not consistent with gradual adjustment to an optimal price. All told, none of the theoretical pricing structures described in Chapter 2 can match the characteristics of prices that are evident in the microeconomic data. This implies that economic models based on these frameworks are very likely to be misspecified. As such, this new UK research is consistent with Angeloni *et al* (2006), who examine the implications of recent evidence on the behaviour of individual prices in the euro area and conclude that several of the most commonly used assumptions in micro-founded models are seriously challenged.

Apart from casting doubt on the viability of these micro-founded theoretical structures for pricing behaviour, the heterogeneity of prices is also a broader concern for policymakers. Even less theoretically rigorous economic models often assume homogenous pricing agents, uniform pricing behaviour, or even 'single price' structures, albeit sometimes implicitly. And even where models attempt to allow some role for relative prices, for instance in Harrison *et al* (2005), the treatment is very simple and falls far short of embracing the degree of

heterogeneity that is evident in the microeconomic data. Of course, economic models are necessarily simplifications of the real world. But, as discussed later, it would be preferable to use a form of model that at least tries to acknowledge the heterogeneity that is evident in prices and other economic variables. As Sinclair and Ellis (2012) note, the adjustment process to a monetary policy shock could display quite a complex time path in an economy where different sectors exhibit different frequencies of price changes. Furthermore, the use of a misspecified model can be a key cause of policy mistakes.

One instance of this relates to a common model used by policymakers to gauge the stance and impact of monetary policy. The standard NKPC results from the literature, presented in Chapter 2, are not compatible with the microeconomic evidence presented in this Chapter and the associated public works. This is a critical issue, as the wrong model can lead to incorrect inference and potentially policy mistakes. Imbs *et al* (2007) demonstrate that, in the presence of genuine heterogeneity in price-setting behaviour across industries, models that assume homogeneous price-setting behaviour will over-estimate the apparent backward-looking behaviour in prices.

Separately, Bidder *et al* (2009) explore what happens when a central bank mistakenly believes that inflation is intrinsically persistent. In their framework, the policymaker believes that prices are indexed to past inflation in periods when firms are unable to re-optimize. If the central bank sets monetary policy optimally, and updates its beliefs gradually, then its beliefs about inflation persistence can be effectively self-confirming in many settings. In other words, because policymakers believe inflation is persistent and set monetary policy accordingly, inflation does appear to be persistent.

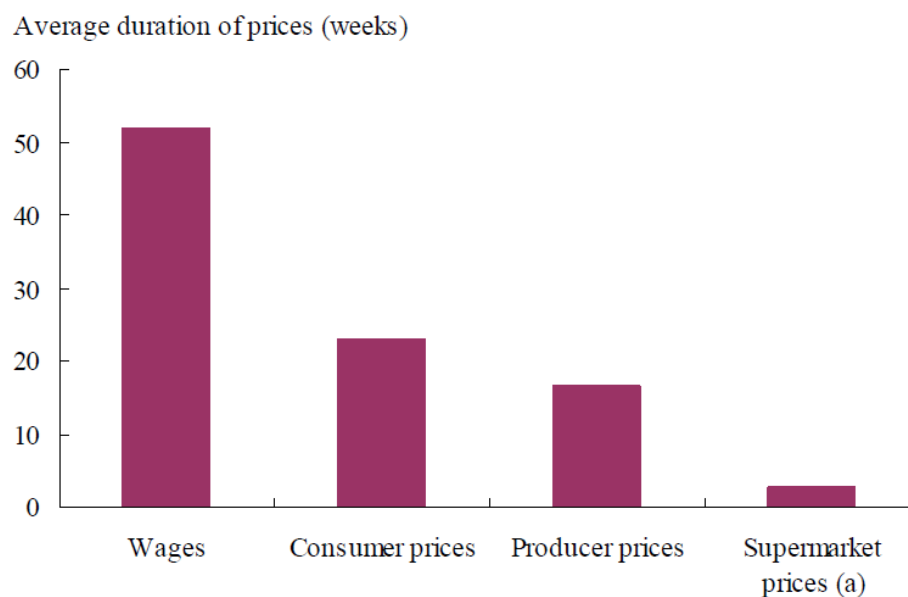
Results from the microeconomic data also have implications for the institutional framework of monetary policy. Fundamentally, this relates back to the role of nominal rigidities. When a shock hits the economy, there are three ways the economy can adjust to that shock: either prices change, quantities do, or both. If prices in the economy were fully flexible, then when demand fell, or productivity changed, firms would be able to adjust those prices straight away, and output and employment would potentially be unaffected. It is precisely because prices do not adjust straight away – consistent with the evidence of nominal rigidity found previously – that a fall in nominal spending can lead to unemployment. By keeping demand in line with supply and controlling inflation, monetary policy can limit the need for large numbers of prices to change, and potentially reduce the cost to the economy in terms of lost output and unemployment when shocks do hit.

This train of thought also relates to what measure of inflation monetary policy should focus on; this issue is discussed in Ellis (2009b). Those markets where the real cost of shocks will be highest are those where prices are the most inflexible – where the nominal side of the economy takes a long time to adjust. In fact, the optimal index for monetary policy to focus on will be an index of the stickiest prices in the economy. Those markets with sticky prices see the biggest changes in real outcomes when shocks hit; in contrast, flexible prices will be able to adjust quickly, limiting the impact on volumes. This result is demonstrated by Aoki (2001), who considers a simple form of price heterogeneity.

Given that asset prices – particularly in financial markets – can change very frequently, the choice of which nominal anchor to use is therefore primarily a distinction between product and labour markets. While the results presented here are consistent with some degree of

nominal rigidity in product markets, in fact that rigidity is far less pronounced than the observed degree of rigidity in labour markets. In particular, Forth and Millward (2000) find that UK wages typically change less frequently than prices in product markets, and hence adjust more slowly to economic shocks (Figure 4.9).

Figure 4.9: Average duration of prices and wages



(a) Based on weekly data; other observations based on monthly data. Wages observation taken from Forth and Millward (2000).

This suggests that the optimal nominal anchor may be wages, instead of prices; Ellis (2009b) discusses this in more detail. However, given past concerns about the measurement of earnings (Turnbull and King, 1999) and the methodological differences between the official measure of Average Weekly Earnings (AWE) and consumer or producer prices (Ellis, 2012), policymakers may still prefer an inflation target based on consumer prices. A relatively specific or esoteric inflation measure, such as one based on AWE, may be harder for people to follow and understand. A more easily recognised index might be preferable, particularly

as there is evidence that the public's views on consumer price inflation are already markedly different from policymakers (Moessner *et al*, 2011).

However, that does not necessarily stop policymakers from putting most weight on conditions in the labour market, as oppose to product markets. It is possible to set monetary policy taking the relative rigidities in product and labour markets into account, even if the headline inflation target is expressed in consumer prices.

This has recently been a live issue for policymakers. Rises in commodity prices – and indeed in the prices of credit and imports (the latter reflecting movements in exchange rates) – are essentially increases in costs for firms. In order to sustain output and employment at their natural levels, real product wages must fall. This will also be necessary if the financial crisis has damaged the level of potential supply (Ellis, 2011). To facilitate this necessary adjustment, one option would be to keep consumer price inflation on target, and force wage inflation below it in order to erode real wages. Alternatively, policymakers could instead keep nominal wage inflation relatively steady, and let consumer price inflation temporarily overshoot. When wages are stickier than prices, the optimal policy response is to let consumer price inflation overshoot. Even if a CPI inflation target is best in presentational terms, policymakers can still spell out how optimal policy depends on the underlying structures of the economy.

Above all, the analysis of microeconomic price data indicates that, if we want to capture the rich heterogeneity of pricing behaviour that we observe in the UK economy and truly understand the impact of monetary policy on prices, it is necessary to embrace more

complex macroeconomic models that do not rely on unrealistic simplifying assumptions about pricing behaviour.

4.4 *How might New Keynesian pricing models be improved?*

One natural question arising from the empirical results is how to improve New Keynesian models to match the behaviour of individual prices. An important step would be to introduce some form of heterogeneity into the model. Typically, full heterogeneous agent models (HAMs) are more complex and intensive than standard representative agent models. In finance, emphasis is often given to simple HAMs incorporating adaptive expectations or other forms of simple heuristics, which are frequently analysed using computational tools alongside analytic methods; Hommes (2006) provides a useful introduction here.

Unfortunately the tractability of HAMs suffers when rational expectations, which are an important feature of DSGE models, are incorporated alongside heterogeneity among economic agents. Heathcote *et al* (2009) provide a review of the rational expectations literature that has developed from the standard incomplete markets (SIM) model, where a large number of agents face idiosyncratic shocks to productivity. The SIM framework implies that agents are identical *ex ante*, but are *ex post* heterogeneous because of the exogenous shocks to income. In a dynamic rational expectations model of this type, agents must form (rational) forecasts of future prices in order to optimise behaviour; but, under the presence of heterogeneity, market-clearing prices become a function of the entire distribution of agents, and literally including this distribution when solving the numerical problem is not feasible. In response to this challenge, Krusell and Smith (1997, 1998) approximate the optimisation problem by assuming ‘near-rational’ behaviour, where agents view prices as evolving according to a finite set of moments of the distribution. But even these techniques are computationally intensive, and there is no guarantee that the

aggregate dynamics that result are close to those in the true rational expectations equilibrium.

Perhaps for these reasons, very little work has tried to incorporate the SIM model in the study of monetary policy. Díaz-Giménez *et al* (1992) is an early example that incorporates agent-level heterogeneity and an explicit banking sector that intermediates both between households and the household and government sectors as a whole. But the non-bank corporate sector is not incorporated into the model, and hence neither is heterogeneous pricing behaviour, and the monetary policy discussion is limited to the impact of a procyclical real interest rate policy on welfare. One avenue for further research could be to further develop this type of model, with heterogeneous firms who employ capital and labour in order to produce goods and services that households then consume. However, such a model is very likely to be computationally and analytically demanding.

Instead, it may be more instructive to incorporate heterogeneity in a somewhat simpler fashion. For instance, Alvarez *et al* (2005) posit the existence of different groups of price-setting firms, each facing different Calvo parameterisations. Under these conditions, they are able to generate downward-sloping aggregate hazard functions, consistent with those in the micro data. Carvalho (2006) also generalises the Calvo model to allow for heterogeneity in price stickiness across sectors, finding that monetary shocks tend to have larger and more persistent real effects in heterogeneous economies, and also that homogeneous-firm models require a substantially lower frequency of price changes in order to match the dynamics of a heterogeneous economy.

An alternative approach, which would lie somewhere between heterogeneous Calvo pricing and a full HAM framework, could be to return to a more general form of price-setting model. For instance, Bakhshi *et al* (2004) demonstrate that, under certain conditions, the state-dependent pricing model of Dotsey *et al* (1999) nests the NKPC. It may be possible to develop this work further. In particular, in Dotsey *et al* (1999) the original form of heterogeneity is imposed via the assumption of a stochastic cost of price adjustment that in effect differentiates firms, which is similar to the exogenous shock to income differentiating households in the SIM model. However, the potential distributional effects arising from this assumption are then ignored by assuming a simple aggregation process to derive the general price level. Instead, it may be possible to use a different approach to map between individual firms' prices and the general price level, such that the model genuinely encompasses the range of pricing behaviour that is observed at the microeconomic level.

A broader implication of this work is that, in the presence of considerable heterogeneity and concerns about the appropriateness of the various micro-foundations that underpin structural pricing models, it is sensible for monetary policy makers to focus on approaches that are robust to these uncertainties. Levine *et al* (2009) make a useful contribution here. The authors set out a comprehensive methodology for designing policy rules in the presence of model uncertainty, and test the robustness of different interest-rate rules. In particular, they find that a rule based on current wage inflation dominates one based on discrete-horizon inflation-forecasts, and also dominates one based on targeting a discounted sum of forward inflation. Furthermore, this result holds regardless of whether the wage inflation rule is designed to be robust or not. This chimes with the previous discussion of relative price stickiness in product and labour markets, and suggests that policymakers may be

better off focusing on such simple – yet very robust – approaches. As such, DSGE models may also need to incorporate different policy response functions than the standard Taylor rule approach discussed earlier.

4.5 *How can tractable models capture price heterogeneity?*

Given the results outlined so far, and the inability of existing pricing frameworks to match the disaggregated data, a remaining challenge is to develop a model that allows for rich heterogeneity in price setting, but is still tractable for UK policymakers. One approach of doing so is set out by Mumtaz *et al* (2009), which is one of the public works accompanying this context statement. This section summarises the paper.

The strategy is to adopt a factor-augmented vector autoregression, or FAVAR, modelling approach. This approach was pioneered by Bernanke, Boivin and Elias (2005). The approach assumes that there are a number of common factors that affect all variables in the economy, which itself is measured as a large data set X_t containing many different series. The common factors or components, C_t , may reflect underlying economic conditions such as 'activity' or 'pricing pressure'. In practice, these factors are estimated as the first K principal components of X_t . These components, or factors, then form the variables that are included in an estimated VAR model: Stock and Watson (2005) examine how many factors should be included in the VAR.

From the resulting VAR estimates, residuals, impulse responses and projections for the original data series can be derived from the eigenvectors associated with the (common) principal components. Using the standard representation, each principle component can be expressed as a linear combination of the underlying data series. Similarly, each data series can be expressed as a linear combination of the principle components, based on a transformation of the eigenvectors associated with each component. When we move back

from the estimated model to the underlying data series, these latter expressions are truncated for each data series, due to the fact that only a limited number of factors are included in the FAVAR. As such, the proportion of variance that remains unexplained by the factors that are included in the FAVAR is not captured. Based on the included factors and the truncated eigenvectors, it is possible to construct impulse responses for individual data series; these are reported in more detail in Mumtaz *et al* (2009).

Regrettably, as access to the disaggregated data was tightly controlled and econometric software was only sparsely available, we were not able to construct a FAVAR based on the microeconomic pricing datasets discussed earlier. Instead, we relied on a less disaggregated dataset that was published externally by the ONS, and hence more readily available. In doing so, our aim was to demonstrate the potential of the FAVAR approach to model disaggregated and aggregate price measures concurrently.

Our data set comprised around 60 macroeconomic UK data series, running from 1977 Q1 to 2006 Q3. It included activity measures such as GDP, consumption and industrial production, various price measures including RPI, CPI and the GDP deflator, as well as money and asset price data. Where appropriate, variables were log-differenced to induce stationarity. In addition to these macro variables, we included a large number of disaggregated deflator and volume series for consumers' expenditure. The Office for National Statistics (ONS) has previously published over 140 subcategories of consumer expenditure data in value, volume and deflator terms, going back to the 1960s (ONS, 2007b). This enabled us to construct a collection of consistent disaggregated consumer price (and volume) data over a suitably long time period; essentially, these data can be thought of as the publicly available

equivalents of the CPI micro data discussed earlier. For instance, the disaggregated data include individual series for furniture repair, dental services, vegetables, electricity and many other components of the consumption basket. By combining these with published (aggregate) price indices such as the CPI and RPI, we can examine how the different aggregate and disaggregated measures of prices relate and behave relative to one another.

As with other VAR models, one critical issue is how to identify economic shocks. In estimating a similar model for the US economy, Boivin, Giannoni and Mihov (hereafter BGM, 2007) first present the FAVAR approach and subsequently identify monetary policy by explicitly including the policy rate (i.e., the Federal funds rate), R_t , as a factor. They then order this variable last, and treat its innovations as monetary policy 'shocks'. This is effectively a version of the Cholesky identification method.

This FAVAR identification scheme is somewhat controversial: Stock and Watson (2005), for instance, express concerns. More generally, the use of the Cholesky identification method in VARs has been criticised by a number of authors, including Canova and de Nicolo (2002) and Uhlig (2005), on the grounds that it may impose a more stringent structure than is borne out by the data. Those authors propose a more flexible identification system based on sign restrictions. In essence, sign restrictions force the initial response of individual variables to be either positive or negative, with no assumptions imposed on the adjustment path that follows (Uhlig, 2005).

One issue is that, in order to use sign restrictions in the context of a FAVAR, some interpretation must be placed on the principal components in the VAR. For example, the

assumption that activity initially falls in response to a negative demand shock requires us to identify one of the common components as an ‘activity’ variable.

In order to enable this economic interpretation, a key innovation of our approach was to partition the dataset of macro variables into different categories, grouping activity, price, money and asset price variables separately. By taking principal components from the resulting partitions within the dataset, we could retrieve common components that were plausibly interpretable as ‘activity’ or ‘price’ factors; for instance, the first principal component of the collection of activity variables could be interpreted as an ‘activity’ factor. This then allows us to use sign restrictions to identify the VAR, and compare it with BGM’s original Cholesky identification method. The sign restrictions that were used to identify the model are set out in Table 4.4 below. We proceeded to estimate two versions of the FAVAR model: one using BGM’s Cholesky approach, and one using our innovation of partitioning the data to allow us to identify the model using sign restrictions. The remaining technical details behind the modelling approach are set out in Mumtaz *et al* (2009), and are not repeated here for brevity.

Table 4.4: Sign restrictions used to identify FAVAR (a)

	Demand shock	Supply shock	Monetary policy shock
Output factor	+	+	-
Inflation factor	+	-	-
Money factor	+	n.a.	-
Asset price factor	+	n.a.	-
Interest rate	+	n.a.	+

(a) Shocks correspond to increases in variables, e.g. an increase in demand, and increase in policy rates.

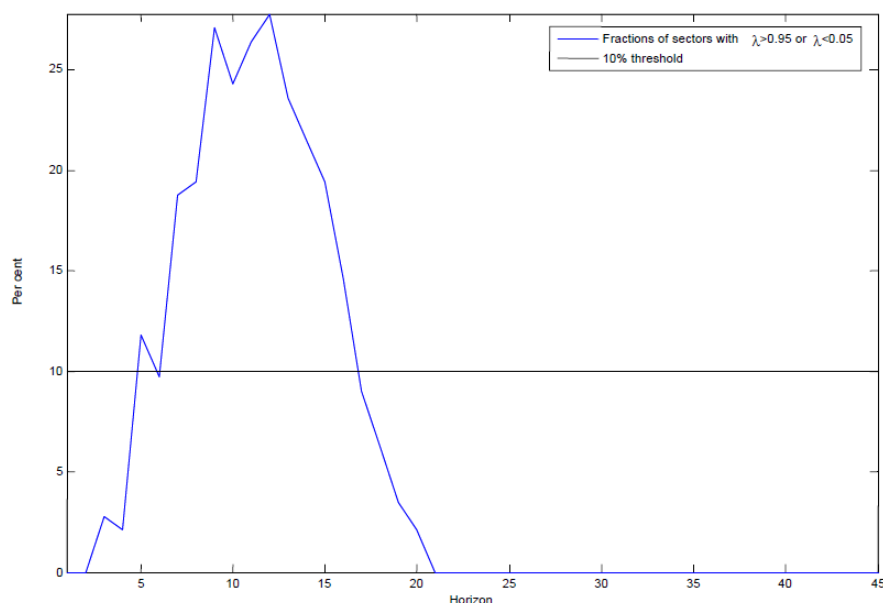
Impulse responses to monetary policy tightening from the Cholesky approach exhibited the usual 'price puzzle' concerns described in Chapter 2, together with a somewhat delayed response of inflation relative to the benchmark results presented in Harrison *et al* (2005). In contrast, impulse responses from the sign restriction model exhibit no price puzzle (by restriction) and the biggest impact on GDP following a monetary tightening is felt after a year or so, consistent with Bank of England (2004). (The sign restriction approach also allows for the examination of supply and demand shocks, in addition to monetary policy.) The estimates from the sign restriction approach were also robust to the shift to inflation targeting in 1992, although standard errors are larger for post-1993 estimates given the smaller data sample.

One considerable advantage of the FAVAR approach is that it allows the examination of the disaggregated dynamics of consumer prices. The two sets of model results were broadly consistent here, exhibiting many different impulse responses among the disaggregated prices, in terms of magnitude and speed of adjustment. Both models suggest that some prices respond immediately to a contractionary monetary policy shock, but other prices take longer to respond, in line with BGM's findings. This suggests that FAVAR models do a good job of capturing the underlying heterogeneity that is evident in the microeconomic price data for the United Kingdom. There are also differences between the models: for instance, the range of disaggregated price responses was wider in the sign restriction model than the Cholesky model. This chimes with previous work by Peersman (2005), who finds that the maximum impact of a monetary policy shock is larger in a sign restriction model than one based on traditional identifying restrictions.

One key question that the FAVAR models can address is the significance (or otherwise) of relative price changes. Because individual prices in different sectors of the economy can change at different times and with different frequencies – and by different magnitudes – it is possible that even a common shock such as an unanticipated monetary policy tightening could affect the distribution of relative prices. If prices do not respond at the same time and in the same manner to a rise in interest rates, then gaps may appear between individual prices (or existing gaps may widen or narrow). In the long run, we would expect any such effects to dissipate, consistent with the view that there is no long-run trade-off between monetary policy and real variables (relative prices can be thought of as ‘real’ prices).

We investigate this phenomenon by examining whether the response of individual price changes was significantly different from average inflation. At a benchmark 10% significance level, we would expect 10% of sectoral price changes to be different from average inflation at any given time. Figure 4.10 shows the proportion of individual sectors where price changes are significantly different from average inflation following a monetary policy shock, based on the sign restriction model. The chart shows that over the short to medium term monetary policy changes do affect the relative price distribution, but these effects are insignificant over the long run. This is consistent with relative price effects exerting significant influence on the dynamics of headline inflation over the course of many months, as observed recently in the United Kingdom.

Figure 4.10: Proportion of price responses different from average inflation (‘sign-restriction’ FAVAR)



In addition to these dispersed impulse responses, we also use the FAVARs to examine the roles that common macroeconomic factors play – measured using the principal components – as opposed to sector-specific factors, which are assumed to wash into the model residuals. In other words, the FAVAR allows us to analyse the extent to which disaggregated inflation rates reflect either macroeconomic or sector-specific developments.

Table 4.5 reports summary statistics on the volatility and persistence of both aggregate and disaggregated quarterly inflation series for the sign restriction FAVAR model. (Encouragingly, these results were very similar in the Cholesky model.) In line with BGM’s results, the majority of the volatility in aggregate inflation rates is due to fluctuations in the common components (the exception being wages, where sector-specific factors matter more). However, for disaggregated inflation measures this is not true: for many disaggregated series, volatility is more commonly due to sector-specific factors, rather than the common

macroeconomic factors. Unsurprisingly, there is considerable heterogeneity among the disaggregated series.

Table 4.5: Volatility and persistence of inflation series ('sign-restriction' FAVAR)

	Standard deviation of			Persistence of:		
	Common component	Sector-specific component	R ²	Series	Common component	Sector-specific component
Selected aggregate series						
CPI	0.86	0.51	0.74	0.80	0.83	-0.21
GDP deflator	0.89	0.45	0.79	0.69	0.81	-0.23
RPI	0.88	0.47	0.78	0.63	0.84	-0.09
Consumption deflator (PC)	0.98	0.20	0.96	0.77	0.84	-0.07
Wages	0.65	0.76	0.42	0.64	0.83	0.20
Disaggregated PC series						
Unweighted average	0.68	0.70	0.49	0.23	0.50	-0.05
Median	0.71	0.71	0.50	0.30	0.58	-0.04
Minimum	0.22	0.31	0.05	-0.51	-0.42	-0.44
Maximum	0.95	0.98	0.91	0.70	0.85	0.53
Standard deviation	0.16	0.15	0.20	0.30	0.30	0.19

There are also marked differences in the persistence of the series. We assessed this by estimating AR(1) models for the common factors and the sector-specific components. In common with BGM, the aggregate inflation measure in Table 4.5 exhibits a high degree of persistence, but the disaggregated series exhibit far less persistence. The AR(1) coefficient for the aggregate consumption deflator was 0.77, but the AR(1) for the median disaggregated series was just 0.30. This is consistent with aggregation bias playing a key role: that is, the persistence of the aggregate consumption deflator is not the average persistence of the underlying component series, but is biased upwards instead.

One important caveat to these results is the use of the first-order autoregressive term as our measure of persistence. In practice, there are several alternative options for gauging persistence, as noted in Fuhrer (2009). These include conventional unit root tests, estimated autocorrelation functions, dominant roots of the univariate autoregressive process, and decompositions of inflation into permanent and transitory components as proposed by Stock and Watson (2007). We use the first-order autoregressive coefficient for simplicity, which is commonly used in other studies as a reduced-form measure of persistence (see for instance Pivetta and Rice, 2007). But as both Fuhrer (2009) and Stock and Watson (2007) note, this reduced form measure of persistence may be affected by structural changes in either the monetary policy regime or the underlying economy. For instance, Stock and Watson (2007) find that these simple reduced-form measures of persistence may exhibit instability if no allowance is made for time variation in lagged coefficients. As such, the reduced-form persistence measures in Table 4.5 may conflate periods of relatively high and relatively low structural inflation persistence.

However, these concerns are less of an issue for the UK micro data presented earlier, as these data samples all start after the introduction of inflation targeting in 1992, and only one data sample – the CPI micro data – starts prior to central bank independence in 1997. In the absence of such structural changes to the monetary policy framework, the behaviour of individual prices is more likely to be truly representative of underlying persistence. And although the reduced-form persistence estimates from the PPI micro data (reported in Bunn and Ellis, 2010) are notably lower than those presented in Table 4.5, the same broad result emerges: individual price changes are much less persistent than the aggregate inflation rate. Furthermore, Bunn and Ellis (2010) also note evidence of aggregation bias in the

disaggregated PPI data.⁷ As such, the broad FAVAR results presented above seem robust to concerns about the precise measure of persistence.

Interestingly, there is little evidence from the FAVAR results that sector-specific factors were important in determining persistence, for either aggregate or disaggregated series. What persistence is present is driven by the common macro components. Furthermore, the fact that these are less important for disaggregated prices than aggregate ones is consistent with disaggregated prices exhibiting less persistence overall. This suggests that any persistence in prices may be driven by persistence in macroeconomic factors, such as activity or policy (as suggested by Bidder *et al*, 2009). It also suggests that sector-specific shocks are transitory and random in nature, consistent with these disturbances playing little role at the aggregate level.

Overall, these findings are in line with those found by Boivin *et al* (2009) for the US economy. While many prices fluctuate in response to sector-specific shocks, these sector-specific shocks tend not to exhibit significant persistence. In contrast, disaggregated prices respond more persistently to aggregate macroeconomic shocks such as monetary policy shocks. The importance of these sector-specific shocks can explain why, at the disaggregated level, individual prices are found to adjust relatively frequently, while estimates of the degree of price rigidity are much higher when based on aggregate data. Meanwhile, the more sluggish responses of disaggregated prices to macroeconomic shocks are consistent with models that assume considerable price stickiness often being successful at replicating the effects of monetary policy shocks. As such, while our model allows for the significant

⁷ The Appendix sets out a simple theoretical basis for aggregation bias in measures of persistence.

heterogeneity in disaggregated prices that is evident in the empirical data, it does not invalidate the baseline assumption of some degree of price rigidity, which is often used in macroeconomic models. This is both consistent with the micro data evidence presented earlier, where even supermarket prices were not found to adjust continuously, and with monetary policy shocks having a significant impact on the real economy in the short to medium term. As in Boivin *et al* (2009), heterogeneity in the behaviour of individual prices does not imply that monetary policy is ineffective.

In summary, a FAVAR modelling approach allows policymakers to capture the rich heterogeneity that is evident in disaggregated pricing data. Our new application of this modelling approach to UK data confirms its viability; and our innovative approach to identification, by partitioning the data and using sign restrictions, also appears to work well. At the same time, our approach still retains the usual stylised facts about the response of macroeconomic variables to monetary policy changes. It also reveals new insights about the role of sector-specific versus macroeconomic factors, and the impact that unexpected changes in monetary policy and other shocks can have on relative prices in the short- to medium-term.

All told, such a FAVAR-based modelling approach will be superior for monetary policy purposes than alternative models that rely on assumptions or restrictions that are not borne out by the evidence from microeconomic price data. Our FAVAR approach allows policymakers to model and understand the interactions between the micro- and macro-economy, and trace the transmission of policy through different sectors as individual prices respond in different ways.

Chapter 5 Summary and conclusions

After painful experiences during the 1970s, a new orthodoxy emerged concerning the institutional design of monetary policy. Rather than leaving interest rates in the hands of politicians, in many countries monetary policy is now delegated to some form of independent central bank. It is striking that while the recent financial crisis and global downturn has led to unconventional policy measures and some debate about the conduct of monetary policy, central bank independence is largely unchallenged.

However, the credibility of monetary policy making institutions is ultimately dependent on their ability to meet their policy objectives – typically, to hit an inflation target. That, in turn, will depend on the tools and analysis that policymakers conduct when setting interest rates and employing other instruments. Worryingly, recent research using microeconomic data has suggested that the standard macroeconomic models that monetary policy makers use fail to match the actual behaviour of prices within economies. This implies that inferences based on such models can be highly misleading.

One gap in the existing literature was the lack of any similar analysis of how individual prices behave in the United Kingdom, and how policymakers should respond to such analysis. This context statement has summarized the data and analysis from a range of public works that address this shortcoming; the public works are included in this submission (following this context statement). A key strength of this analysis was access to extensive and unique datasets of individual UK prices, which had not been used before. Importantly, this included both the individual prices that are collected for the purposes of compiling and publishing

aggregate inflation indices such as the CPI and PPI; and private sector data collected directly from the point of sale at major supermarkets around the country. The depth and breadth of these datasets is unparalleled in other research on UK prices. At the same time, the highly confidential nature of these data meant that access arrangements were very tightly controlled.

The subsequent analysis of these data revealed a remarkable degree of heterogeneity in terms of how individual UK prices behave. Importantly, this heterogeneity is essentially ignored by typical macro models; at the same time, the standard theoretical frameworks that underpin ‘micro founded’ models also fail to fit the empirical facts. As such, this original research reveals some fundamental failings in the design and application of monetary policy models. If policymakers are unaware of the heterogeneity in pricing behaviour and are unable to identify relative price movements, then they risk inflicting unnecessary damage on sectors where prices change relatively infrequently.

Instead, a different approach is required; policymakers need to be able to combine heterogeneity with tractability. One way to meet these requirements is to employ the recent ‘factor augmented vector autoregression’ (FAVAR) modelling methodology previously used in the United States. Unfortunately it was not possible to replicate this using the extensive microeconomic pricing datasets due to data access restrictions. But, using a database of disaggregated consumer prices, we were able to apply the FAVAR approach to UK data for the first time. Importantly, we also propose and implement an alternative identification scheme that avoids well-documented concerns about using the standard Cholesky ordering. This innovation is a key contribution from our research.

To conclude, this context statement summarizes a body of work that fills a clear gap in the economic literature; despite much work examining the behaviour of individual prices in other countries, no comparable work had been compiled for the United Kingdom. After sourcing and gaining access to extensive and previously unexploited individual price data from different sources, the analysis herein then uncovers for the first time the true extent of the rich heterogeneity in the behaviour of UK prices within and across sectors. The findings from this original analysis pose significant challenges for theoretical pricing frameworks and modern macroeconomic models. Happily, the public works also demonstrate that it is possible for policymakers to capture this rich heterogeneity within a useful and tractable modelling framework. As such, the collected works offer a genuine and original contribution to economic research in this field.

Appendix: The role of aggregation bias in measures of persistence

One of the key results from Mumtaz *et al* (2009), cited in the main body of the context statement, is the marked difference in the persistence of aggregate versus disaggregated inflation series. In particular, aggregate inflation measures exhibit a high degree of persistence, but the disaggregated series exhibit far less persistence. This result is consistent with aggregation bias playing an important role: that is, that the persistence evident in aggregate price indices is not the average persistence of the underlying component prices, but is biased upwards instead. This Appendix sets out a simple theoretical basis for general aggregation bias in measures of persistence; I am very grateful to Charlie Bean for originally demonstrating this point.

Suppose that the variable e_t is the sum of two independent AR(1) processes:

$$e_t = \frac{u_t}{1 - \rho L} + \frac{v_t}{1 - \phi L}$$
$$e_t = u_t + \rho u_t + \rho^2 u_t \dots + v_t + \phi v_t + \phi^2 v_t \dots$$

It follows that:

$$\sigma_e^2 = \frac{\sigma_u^2}{1 - \rho^2} + \frac{\sigma_v^2}{1 - \phi^2}$$
$$\text{Cov}(e_t, e_{t-1}) = \frac{\rho \sigma_u^2}{1 - \rho^2} + \frac{\phi \sigma_v^2}{1 - \phi^2}$$
$$\text{Corr}(e_t, e_{t-1}) = \left(\frac{\rho \sigma_u^2}{1 - \rho^2} + \frac{\phi \sigma_v^2}{1 - \phi^2} \right) / \left(\frac{\sigma_u^2}{1 - \rho^2} + \frac{\sigma_v^2}{1 - \phi^2} \right)$$

Suppose now that:

$$\sigma_u^2 = \sigma_v^2$$

which implies that:

$$\begin{aligned}
Corr(e_t, e_{t-1}) &= \left(\frac{\rho}{1-\rho^2} + \frac{\emptyset}{1-\emptyset^2} \right) / \left(\frac{1}{1-\rho^2} + \frac{1}{1-\emptyset^2} \right) \\
&= \frac{\rho + \emptyset - \rho\emptyset^2 - \emptyset\rho^2}{2 - \rho^2 - \emptyset^2}
\end{aligned}$$

Now suppose that the AR terms are equally spaced around a common average:

$$\rho = \varphi - \alpha$$

$$\emptyset = \varphi + \alpha$$

where $\alpha > 0$. It then follows that

$$\begin{aligned}
Corr(e_t, e_{t-1}) &= \frac{2\varphi - (\varphi - \alpha)(\varphi + \alpha)^2 - (\varphi + \alpha)(\varphi - \alpha)^2}{2 - (\varphi + \alpha)^2 - (\varphi - \alpha)^2} \\
&= \varphi + \frac{\alpha(\varphi + \alpha)^2 - \alpha(\varphi - \alpha)^2}{2 - (\varphi + \alpha)^2 - (\varphi - \alpha)^2} \\
&= \varphi \left(1 + \frac{4\alpha^2}{2 - (\varphi + \alpha)^2 - (\varphi - \alpha)^2} \right) > \varphi
\end{aligned}$$

Hence, the estimate of persistence in the aggregate series will be higher than the average persistence in the two component series.

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HOW DO INDIVIDUAL UK PRODUCER PRICES BEHAVE?*

Philip Bunn and Colin Ellis

This article presents a number of stylised facts about the behaviour of individual UK producer prices. First, on average 26% of prices change each month, although there is considerable heterogeneity between sectors. Second, the probability of price changes is not constant over time. Third, the distribution of price changes is wide, although a significant number of changes are relatively small. Fourth, prices that change more frequently do so by less. Conventional pricing theories struggle to match these results, particularly the marked heterogeneity.

Nominal rigidities imply that prices cannot adjust freely. In particular, the degree of nominal rigidity in the economy will influence the short-term impact of monetary policy on real activity and the response of inflation to changes in policy. The notion of nominal rigidity is a feature of many economic models. A variety of mechanisms have been put forward to explain this assumption but these can often have differing policy implications. Until recently, there was little work examining what the data suggest about the nature of these nominal rigidities.

One approach to assessing how prices are set is to analyse large data sets of individual prices. These are typically the micro data sets used by statistical offices to construct aggregate price indices. These data sets have the advantages of containing a very large number of price quotes and they allow analysis of price-setting behaviour across different types of prices in the economy and analysis of how prices are set over time. Bils and Klenow (2004) for the US and Dhyne *et al.* (2006) for the euro area are examples of studies that have used this type of approach and consumer price data. Nakamura and Steinsson (2007) and Vermeulen *et al.* (2007) report similar results using producer price data but there is little similar work using large microdata sets to assess how prices are set in the UK.

This article presents some new work that examines pricing behaviour in the UK using microdata that underpin the UK Producer Prices Index. Unlike consumer price indices, which are based on the prices that households pay for goods and services, producer prices measure the prices that are charged by the firms that actually produce goods (which are then sold on by retailers to consumers). As such, they provide information on how prices behave at an earlier point in the supply chain than consumer prices do. One resulting feature of these data is that temporary and short-lived promotions are

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The views expressed in this article are those of the authors, and not necessarily those of the Bank of England or the BVCA. We thank the ONS for making the data available to us. We are also grateful to Neal Hatch, Steve Millard, Nick Oulton, seminar participants at the Bank of England and an anonymous referee for the Bank of England working paper series, two anonymous referees for this Feature and Steve Machin for useful comments. This work contains statistical data from ONS which is Crown copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research data sets which may not exactly reproduce National Statistics aggregates.

typically less prevalent in producer price data than in consumer price data. A companion article (Bunn and Ellis, 2011) examines the properties of UK consumer prices separately.

The data we use are for output prices in the manufacturing sector and have been made available by the Office for National Statistics (ONS). This article is the first to make use of this data and is the first UK study, along with our examination of consumer price data (Bunn and Ellis, 2011), to use price microdata underlying recent aggregate inflation statistics to investigate the extent of pricing rigidities in the UK. The only previous work using individual price quote data for the UK that we are aware of is a study of manufacturing prices in the late 1950s and early 1960s (Godley and Gillion, 1965).

The article starts by setting out the details of the data used. It then presents a number of stylised facts about both the frequency and size of changes in UK producer prices and draws comparison with corresponding results for the US and euro area. The article also looks at the relationship between the frequency and magnitude of price changes. Finally, it assesses how the results relate to different price-setting theories before concluding.

1. The Data

The data we use are individual producer price quotes, collected by the ONS. These price quotes are the prices of individual products produced by individual firms in each particular month. The quotes are weighted and aggregated to form price indices, such as the UK Producer Prices Index (PPI). All the underlying data were accessed and analysed using the ONS' Virtual Microdata Laboratory (VML). Ritchie (2008) describes the history of the VML, and the detailed terms and conditions that apply to users.

The data are output prices – that is, the selling prices of manufacturing companies of products destined for sale in the UK. Although inflation measures based on consumer prices are the series typically targeted and monitored most closely by central banks it is pricing decisions made by producers that are often modelled by economists in macroeconomic models. Producer prices are the prices charged by firms actually producing goods rather than the prices charged by retailers selling goods to consumers. Examining producer prices allows us to investigate the extent of pricing rigidities at an earlier point in the supply chain than would be the case using consumer price data.

The ONS collects the underlying producer price data at a monthly frequency: our sample covers the period between January 2003 and December 2007, as weights were not available over a longer backrun of data. In total, the final data set that our analysis is based on included approximately 430,000 individual producer price quotes, covering 18,000 products produced by 9,000 firms. A product is uniquely defined as being a principal output of the reporting firm(s), and as such the data are reliant on firms reporting on a consistent basis over time. Data are available at the individual product-firm level – that is, price observations are supplied for each specified product for each firm in the sample.

As firms and products enter and exit the sample on a frequent basis, the panel is not balanced and therefore price quotes are not available for every item in each period.

This partly reflects the ONS policy of rotating survey samples, particularly for smaller firms. Unfortunately, the precise reason for an item leaving the sample is not available. But we do know that the sample is updated annually to incorporate new products and changes in demand patterns for existing products, and that the methodology used for updating the PPI data means that around a third of the sample should be rotated every year. As such, the relatively frequent entry and exit of individual products and firms is likely to reflect regular sample rotation as well as non-response and other concerns. Overall, the high turnover rate means that around 10% of items are present in our data set for all 48 months – on average, an item is in the data for around 24 months, or two years.

Imputed observations and a negligible number of ‘zero’ price quotes are excluded from the data, as it is important to focus only on actual price quotes in trying to understand price-setting behaviour.¹ Given that the price of each item is only collected once a month, we can only examine price changes at this frequency: so if a price changes within a given month that will not be captured in our data. This means that our estimates of how often prices change may be biased: we may overestimate the time between changes in manufacturing output prices if intra-month price changes are excluded from the analysis. We are not able to explicitly identify temporary price promotions or special offers in the data, although these may be less prevalent in manufacturing output prices than in retail consumer prices.

Unless otherwise stated, the results in the article are presented on a weighted basis. The weights represent the individual weight of each particular item in each month in the aggregate producer price index published by the ONS. These weights are based on sales within the UK.

All our results take the underlying PPI microdata to be a true reflection of prices. In practice, the data will be subject to both sampling and non-sampling error, as described in ONS (2008). One particular issue could be a specific form of non-sampling error: the underlying PPI survey asks respondents about their ‘normal transaction price’, which should be the price manufacturers achieve in a significant proportion of UK sales and representative of current output. If survey respondents find it difficult to report ‘like with like’ prices each month, this could introduce errors into the raw microdata. These prices are also ‘average’ prices over the month rather than the price on a single day. However, given the immense difficulties in identifying and compensating for these errors, we assume that the underlying microdata is accurate. The next Section presents results from our analysis of the data.

2. How Often do Prices Change?

2.1. *Aggregate Frequency of Price Changes*

Approximately one in four UK producer prices change each month. Table 1 shows that an average of 26% of prices changed each month between 2003 and 2007. This is calculated as the total number of price changes divided by the total number of price

¹ Approximately 3% of the raw sample is imputed. The ONS impute data where actual price quotes were not available, in most cases the imputed price is simply the price from the previous month carried forward.

quotes; we drop quotes where there is no information on the price in the previous month because we are unable to measure whether the price has changed for these observations. A large proportion of prices do not change every month, although for some firms it may be that they review their price each month and decide not to change it rather than that the presence of nominal rigidities prevents them from adjusting their price. Of the price changes we observe, approximately 60% are price increases and 40% are decreases. The data are relatively consistent across individual years; the share of prices changing in each year is always between 24% and 28%, suggesting that our results are not highly sensitive to the sample period. Section 2.4 contains further discussion of price flexibility over time.

Our results suggest that prices change more frequently than the only other previous UK study using individual output price data (Godley and Gillion, 1965). But that work covered a much earlier period: it was based on a sample of 470 manufactured products between 1955 and 1961, and it found that the average interval between prices changes was around two years. Our results are very similar to those for UK consumer good prices from our companion article (Bunn and Ellis, 2011). On average, 24% of consumer goods prices were found to change each month, very close to the 26% of producer prices changing in this study. The finding that prices charged by goods producers change with similar frequency to those charged for retail goods suggests that few pricing frictions exist between the production and retail sectors in the UK.

UK producer prices appear slightly more flexible than in the euro area. Vermeulen *et al.* (2007) find that 21% of producer prices change in the euro area each month, compared with 26% in the UK. Looking at the evidence from the individual euro-area countries, the frequency of price change in France is similar to that in the UK but estimates for other euro-area countries are lower. Producer prices in the UK appear to have a similar degree of flexibility to prices in the US. Nakamura and Steinsson (2007) report that 25% of finished goods and 27% of intermediate goods change each month in the US, both very close to the UK Figures.

It is difficult to make strong statements about the causality of price changes from comparing price adjustment frequencies across countries. But it is possible that a

Table 1
Percentage of Producer Prices That Change Each Month

	All changes	Increases	Decreases	Period covered
UK	26	16	10	2003–7
Euro area weighted average	21	12	10	
Belgium	24	13	11	2001–5
France	25	14	11	1994–2005
Germany	22	12	10	1997–2003
Italy	15	9	7	1997–2002
Portugal	23	14	10	1995–2000
Spain	21	12	9	1991–9
US				
Finished goods	25	–	–	1998–2005
Intermediate goods	27	–	–	1998–2005

Notes. Euro-area data are taken from Vermeulen *et al.* (2007). The US data come from Nakamura and Steinsson (2007).

greater degree of price flexibility in the UK compared with the euro area could reflect a lower incidence of contracts, implicit or otherwise, or possibly its role as a small open economy with its own currency.² The data also cover different time periods, which could also account for some differences in the estimated frequency of price changes across countries, although the sample time frames used in most studies are generally characterised by relatively low and stable inflation.

2.2. *Duration of Prices*

The simplest way of calculating the duration between price changes is to take the inverse of the mean share of prices that change each month. Using this simple measure, roughly a quarter of prices change each month and the average time between prices changes is 3.9 months.³ But this summary statistic masks a wide distribution of price frequencies.

In the presence of heterogeneity, it has been shown that the mean frequency of price change can overstate aggregate price flexibility (Nakamura and Steinsson, 2010). Because of the concavity of the duration–frequency relation, from Jensen’s inequality, averaging after item-level inversion will yield higher duration estimates than averaging across items before inversion, unless all frequencies are identical. We therefore consider a second a method of calculating the duration that is designed to exploit the variation across products. We calculate the average number of months between price changes for each individual item (the number of months each item is in the data divided by the number of price changes), and then average these duration statistics across all items – in that regard, this approach is similar to calculating hazard functions. Based on this second approach, the mean number of months between price changes per item is 10, significantly higher than the four months from the inverted mean frequency of price changes. The median number of months between price changes per item is seven months.

The difference between the results from these two methods is a function of the heterogeneity that is readily evident in the data set. Figure 1 shows the distribution of the average durations for the individual items, using the weights of individual items in the pooled data across the five years of the sample. Fourteen per cent of items have an average time between price changes of between one and two months; this covers the items that change price very frequently and includes many of the energy and commodity based products. The second largest group covers items that have an average time between price changes of 11–12 months, this mainly includes products that tend to change price on an annual basis. For 75% of items, the average number of months between price changes is 12 months or less.

Our work on the PPI microdata implies that prices change more frequently than the results from the recent Bank of England pricing survey (Greenslade and Parker, 2010). The survey found that the median firm in the manufacturing sector only changes price once a year. The pricing survey results are most comparable to our second method of calculating average durations of prices across items, where we find that the median

² For example, Buisan *et al.* (2006) find evidence that is consistent with UK manufacturers (exporters) having a lesser degree of price-setting power than in the euro area, which could also manifest in more frequent price changes.

³ This calculation of the average duration implicitly assumes homotheticity; see Baudry *et al.* (2007).

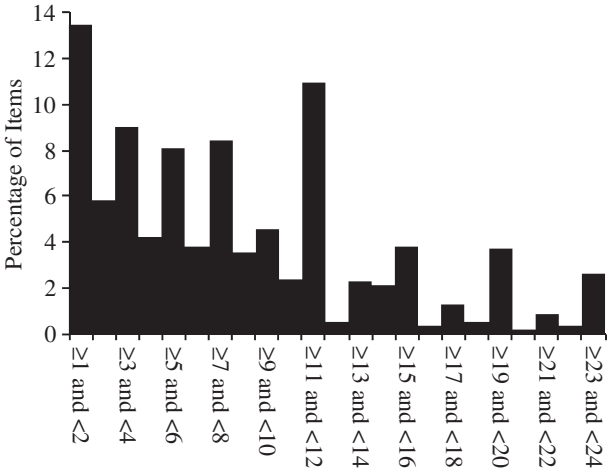


Fig. 1. *Distribution of Number of Months between UK Producer Prices Change per Item*

number of months between price changes per item is seven, less than the 12 months in the price-setting survey.

2.3. *Frequency of Price Changes by Product Group and Industry*

There is substantial variation in the frequency of UK producer price changes between different sectors and product groups (Table 2). The prices of energy products (petrol and fuel in our sample) change the most frequently, with an average of 87% of all prices changing in any given month. The prices of consumer food products and intermediate goods change more frequently than the prices of consumer durables and consumer non-food non-durables. Around 40% of price changes are cuts for each of the product groups.

The product groupings used in Table 2 are the same as those employed for the euro area by Vermeulen *et al.* (2007). Producer prices in the UK appear to be a little more flexible than in the euro area for all of the six categories. The UK ranking of the different groups is similar to that in the euro area. Energy products have by far the most flexible prices, followed by consumer food products and intermediate goods.

There is also substantial variation in the frequency of price changes at the major industry level (Figure 2). Prices of textiles and clothing products change least often among all of the Standard Industrial Classification (SIC) industries, followed by furniture prices. The prices of petrol and fuel, secondary raw materials, basic metals products and other non-metallic mineral products all change significantly more frequently than average. These are all products where a relatively high proportion of manufacturers’ costs are likely to be accounted for by basic commodities that are traded and whose price changes daily. The finding that heterogeneity is important is consistent with work for the euro area (Vermeulen *et al.*, 2007) and the US (Nakamura and Steinsson, 2007) and with survey evidence for the UK (Greenslade and Parker, 2010).

To investigate further the possible relationship between the frequency of price changes and the type of inputs used in the production process we used the ONS Supply

Table 2
Percentage of Producer Prices That Change Each Month by Product Group

	All changes (UK)	Increases (UK)	Decreases (UK)	All changes (euro area)
Energy products	86.9	56.3	30.6	72
Consumer food products	27.1	15.2	12.0	22
Consumer non-food non-durables	13.1	7.6	5.5	11
Consumer durables	15.6	9.5	6.1	10
Intermediate goods	25.4	15.2	10.2	22
Capital goods	18.8	11.0	7.8	9

Note. Euro-area data are taken from Vermeulen *et al.* (2007).

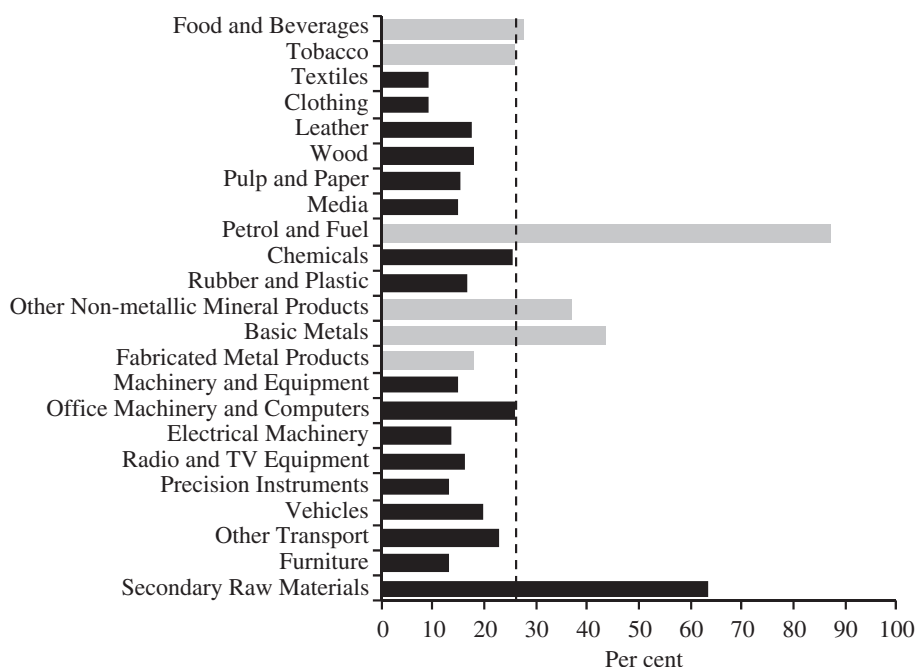


Fig. 2. *Percentage of UK Producer Prices that Change Each Month by SIC Industry*
Notes. The dotted line shows the average for the whole sample. The light-shaded bars are industries which have more than 25% of inputs from agriculture, energy extraction and supply, iron, steel and non-ferrous metals.

and Use tables to look at the proportion of inputs for each industry from primary industries (agriculture, energy extraction and energy supply), iron and steel and non-ferrous metals. There were six industries with more than a quarter of inputs from these sectors, indicated by the light-shaded bars in Figure 2. Four of these (food and beverages, petrol and fuel, other non-metallic mineral products and basic metals) are among the five industries with a higher than average share of prices changing each month. Secondary raw materials, or recycling, is the other industry with a very high share of prices changing each month. The inputs come from across a range of

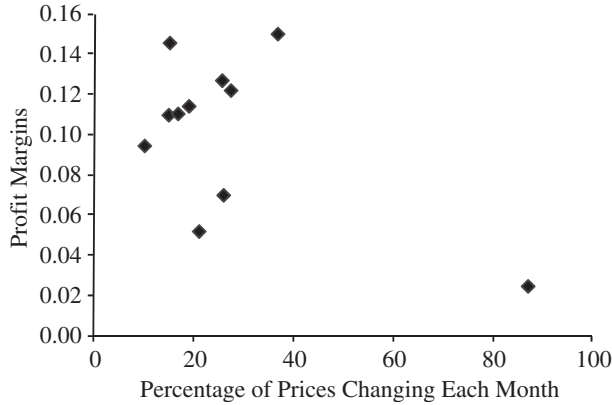


Fig. 3. *Frequency of UK Producer Price Changes and Profit Margins*

Note. Profit margins are defined as gross operating surplus divided by gross output.

industries, but the nature of the output means that output prices are also likely to be closely linked to prices in commodity markets.

We also considered whether there was any correlation between the frequency of price changes by industry and particular industry characteristics from the Bank of England Industry Database (BEID).⁴ One hypothesis might be that firms with higher profit margins may need to change price less frequently if they have more scope than firms with lower margins to accommodate changes in their costs. But Figure 3 suggests that there is no clear relationship between the level of profit margins and frequency of price change. We typically think that labour costs change less frequently than some of the other costs faced by firms, so we also considered the relationship between the share of prices

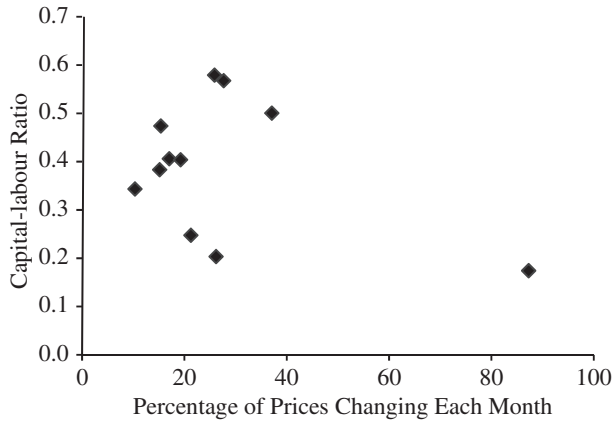


Fig. 4. *Frequency of UK Producer Price Changes and Capital-Labour Ratios*

Note. Capital-labour ratios are defined as capital services divided by quality-adjusted labour input.

⁴ We aggregated some of the industries together to match up to the 10 BEID manufacturing industries so that we were able to make direct comparisons between our results and the BEID data. For more information on the BEID, see Groth *et al.* (2004).

Table 3
Percentage of Producer Prices That Change by Calendar Month

	All changes	Increases	Decreases
January	30.8	19.1	11.8
February	25.2	15.6	9.6
March	25.7	18.3	7.4
April	27.8	17.6	10.2
May	26.9	16.3	10.6
June	25.4	13.8	11.7
July	25.9	16.7	9.2
August	25.0	14.6	10.3
September	25.8	15.0	10.8
October	26.6	16.0	10.7
November	24.4	13.3	11.0
December	22.9	11.6	11.3

changing and the capital to labour ratio to see if firms who are more intensive users of labour changed price less often. But again, there was no clear relationship (Figure 4).

2.4. Changes in Price Flexibility Over Time

There is well-known seasonality in prices, and that is clear in the producer price data. Prices are most likely to change in January and April and least likely to change in November and December (Table 3). The frequency of price changes is not constant over time in our sample. The average proportion of prices changing each month increased every year between 2003 and 2007, rising from 24% in 2003 to 28% in 2007. This reflects a greater share of prices increasing each month, since the share of prices falling has been relatively stable.

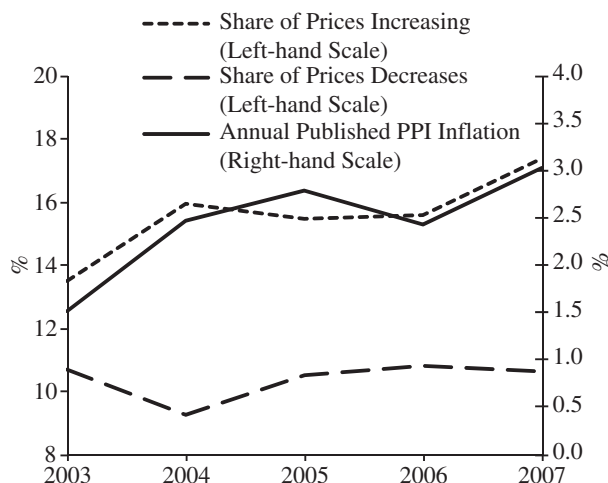


Fig. 5. *Producer Price Index (PPI) Inflation and Percentage of UK Producer Prices Changing Each Month*

Overall inflation rates can increase if either a higher proportion of prices rise each month (or if fewer prices fall) or if the prices that do rise increase by more (or if the prices that are reduced fall by less). Figure 5 shows that there is some correlation between the annual average share of prices increasing each month and the aggregate producer price inflation rate.⁵ However, there is little relationship between the share of prices falling and overall inflation. The presence of a relationship between the frequency of price changes and aggregate inflation makes it difficult to draw firm conclusions about changes in underlying producer price flexibility. It may simply be that rising input costs forced more firms to increase their prices in the latter part of the sample.

3. Hazard Functions

The analysis presented so far has concentrated on the average frequencies of prices changing, which can be interpreted as unconditional probabilities of price changes. We also consider the conditional probabilities – the hazard functions. These functions are calculated as the share of price changes observed for firms or products in the current period, divided by the share of prices that have not changed in previous periods. As such, they indicate what the probability of a price change occurring is, given that we know how long it has been since the previous change.⁶

We only use items that have at least one price change in our estimation of the hazard functions, items whose price never changes are excluded from the analysis. We only use each item once in the hazard function estimation, using the time between the first and the second price change (if there is one). This means that the hazard functions are representative of the probability of the price changing for the average item rather than of the average price change.

Figure 6 shows the estimated hazard functions for UK producer prices. It shows a simple unweighted version in which all items are given the same weight and a weighted version which is calculated by assigning weights to each item based on their weight in the pooled sample across the 2003–7 period. Weighting makes relatively little difference to the hazard function. The hazard function for producer prices has a large spike at one month; this implies producer prices are most likely to change in the month after they previously changed. Thereafter, the probability of a price change drops significantly. This indicates that, if a price is unchanged in the first month after it has previously changed, it is also likely to remain unchanged in the following month.

There are spikes in the hazard functions at 4 and 12 months. The spike at 12 months suggests that some firms only adjust their prices on an annual basis. There is also a more modest tick up at 24 months, which could also be consistent with annual pricing reviews. Other than the spikes identified above, the hazard function is relatively flat, although there is perhaps a very modest downwards slope. The hazard rate never falls significantly below 5% over the two-year window shown in Figure 6.

The shapes of these hazard functions are broadly consistent with those drawn for other countries in similar micro-price studies. Álvarez *et al.* (2005) report a set of

⁵ Published PPI inflation rates used in this article are taken from a vintage of data from before the (2005 = 100) rebasing exercise since the weights supplied to us were consistent with the previous base and weighting.

⁶ More technical detail on hazard functions is presented in Bunn and Ellis (2010).

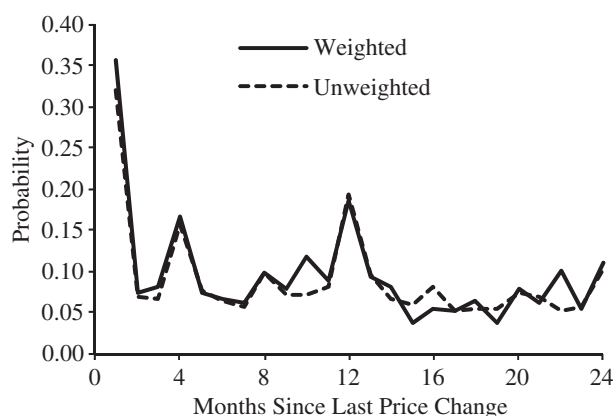


Fig. 6. UK Producer Price Hazard Function

stylised facts that are present in estimated hazard functions for a number of euro-area countries and for the US using data on both consumer prices and producer prices. These facts are that hazard functions are downward sloping, the hazard rates are not zero in any period, and that there are spikes at 1 and 12 months. Our hazard functions for UK producer prices clearly fit the last three facts, although the first is more debatable.

One concern with aggregate hazard functions is that they can potentially be misleading in the presence of cross-sectional heterogeneity. In particular, Álvarez *et al.* (2005) demonstrate that, when different groups of price-setters behave differently, it is possible to generate an aggregate hazard function that is distinct from the processes that individual groups of price setters follow. Dias *et al.* (2007) also show that bias can ensue in the presence of heterogeneity. In light of this, we also calculated separate hazard functions for each of the different product groups (Figure 7).⁷ The hazard function for energy products is not shown because there are relatively few items in this group and most change price within the first few months. All of the product level hazard functions look relatively similar and have spikes in the same places. So whilst there is still likely to be heterogeneity in the behaviour of prices within product groups, at this level of disaggregation, the degree of cross-sectional heterogeneity in the hazard functions is not particularly marked. The spike at one month is largest for food products and intermediate goods, while the one-year spike is biggest for capital goods.

4. Magnitude of Price Changes

The distribution of the size of price changes is wide, with a number of large price changes. But the distribution is not uniform, there are also a large proportion of price changes that are relatively small and close to zero. Just under 30% of all price changes are between 1% and -1%, about 45% are between 2% and -2%, 70% are between

⁷ The unweighted hazard functions are shown because as the sample sizes get smaller towards the end of the two-year window the weighted versions start to become more volatile as they are dominated by small numbers of items with high weights.

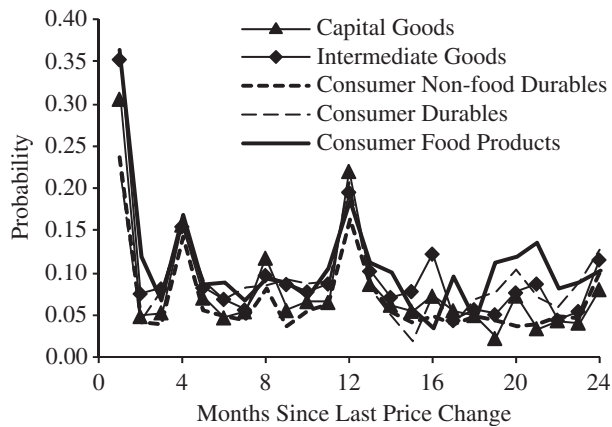


Fig. 7. UK Producer Price Hazard Functions by Product Group (Unweighted)

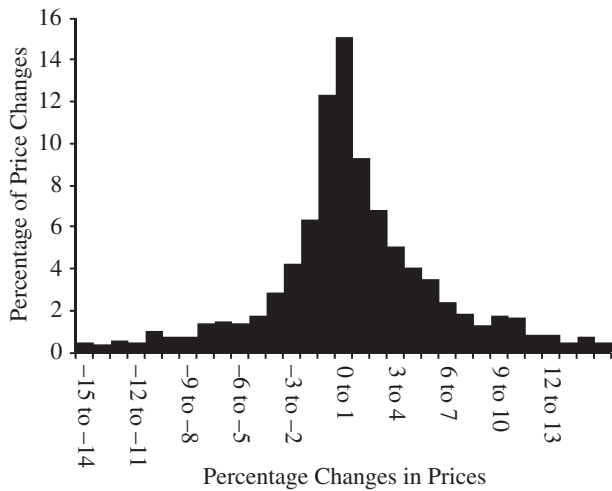


Fig. 8. Distribution of Magnitude of UK Producer Price Changes

Notes. Price changes are grouped into one percentage point intervals. The distribution only includes observations where the price changes.

–5% and 5%, and 90% are between 15% and –15%. Figure 8 shows the distribution of the size of price changes, while Table 4 summarises some key percentiles in the distribution. The large share of price changes that are price falls and the large proportion of price cuts that are smaller than 5% suggests that there is limited evidence to support the presence of downward nominal rigidities in product markets in the UK.

The broad shape of the distribution of the size of price changes appears similar to that from earlier work by Godley and Gillion (1965) in the non-engineering industries in the UK in the late 1950s and early 1960s. The distribution of producer price changes in the UK appears to be a little wider than in the euro area. Vermeulen *et al.* (2007) show that the 75th and 90th percentiles in the distribution of price increases in the euro area are 5% and 13% respectively, which compares to 7% and 19% for the UK.

Table 4
Distribution of Percentage Changes in UK Producer Prices

	All changes	Increases	Decreases
5th percentile	-12.1	0.1	-23.8
25th percentile	-1.3	1.0	-6.6
Median	0.6	2.9	-2.3
75th percentile	3.8	6.6	-0.7
95th percentile	14.3	19.4	-0.1

Similarly for the distribution of price decreases, the distribution in the euro area is not as wide as in the UK. The 75th and 95th percentiles for the euro area are 5% and 14%, lower than the corresponding figures of 7% and 24% for the UK. Among the individual euro-area country results reported in Vermeulen *et al.* (2007), only Portugal is found to have a wider distribution of the size of price changes than the UK.

There is significant variation across industries in the proportion of price changes that are relatively small. Figure 9 illustrates the share of prices changes that lie between -2% and 2% by industry.⁸ There tend to be fewer small price changes and hence more large changes in the prices of energy goods than for other products. The larger changes in energy prices could be explained by the volatility in and the size of changes in oil prices over our sample period: oil prices roughly trebled between the start of 2003 and the end of 2007. In Figure 9, industries are sorted from top to bottom according to the share of prices that change each month. Excluding energy products, there seems to be no clear relationship between the share of price changes that are small in percentage terms and the frequency of price changes across industries.

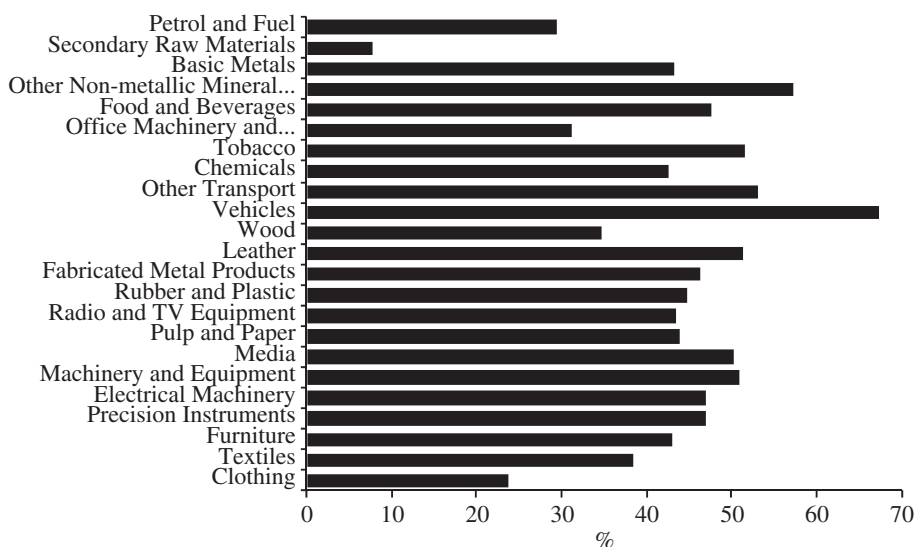


Fig. 9. *Percentage of UK Producer Price Changes between -2% and 2% by SIC Industry*

⁸ The differences across industries look similar if we choose a different measure of small price changes such as -1% to 1% .

Table 5
Distribution of Percentage Changes in UK Producer Prices by Year

	5th percentile	25th percentile	Median	75th percentile	95th percentile
2003	−13.3	−1.7	0.4	3.3	13.1
2004	−11.7	−1.1	0.9	4.3	13.9
2005	−11.7	−1.4	0.5	4.1	15.0
2006	−12.6	−1.6	0.5	3.0	12.6
2007	−10.0	−0.9	0.6	4.1	14.3

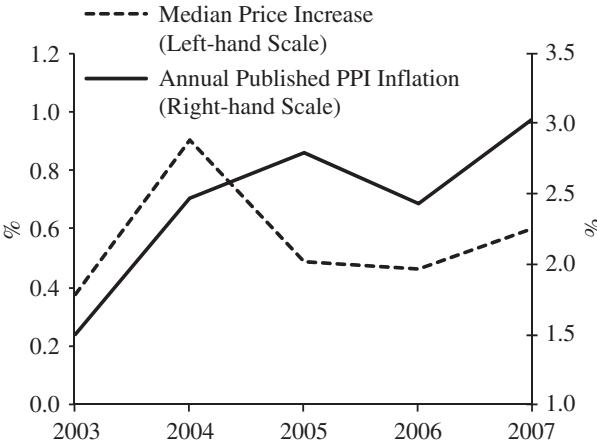


Fig. 10. *Median UK Producer Price Change by Year*

The distribution of the size of price changes by year is relatively similar in each of the five years of our sample (Table 5). There is a positive correlation between the median price change and aggregate inflation rate, and between the percentiles of the distribution shown in Table 5 and the change in published PPI. Figure 10 shows the relationship between the median price change and aggregate PPI inflation.⁹ Combined with the earlier results on the frequency of price change over time, this implies that periods of higher aggregate inflation rates are characterised by both a higher proportion of prices changing and by those prices that do change increasing by more than in periods of lower inflation.

5. Correlation Between the Frequency and Magnitude of Price Changes

Bringing together information on the frequency and magnitude of price changes at the micro level, we find that the average size of price changes is smaller for items that change price very frequently. If prices can be changed without cost in any period, there is no reason why price changes should be larger the longer it is since the previous price

⁹ We report the median rather than the mean price change because the median is arguably more representative of the average price change. Movements in the mean price change from the microdata appear to be influenced to some extent by large price changes by a small number of observations in the tails of the distribution.

change. The finding that price changes tend to be smaller for items that change price frequently would be consistent with either some costs of adjustment or the presence of constraints which only allow or incentivise firms to change prices at infrequent intervals.

Figure 11 shows a scatter plot of the size of the average price change against the number of months since the previous change. For periods of up to one year there is a strong positive correlation between the average size of price changes and the time since the previous change. For price changes that take place no more than three months since the previous change, the median price change is around 0.5%, but for price changes that take place one year since the previous change, the median price change is approximately 3%. Beyond one year since the previous price change, the correlation between the frequency and magnitude of price changes appears to break down, although the sample size for this group is substantially smaller. This is especially true as

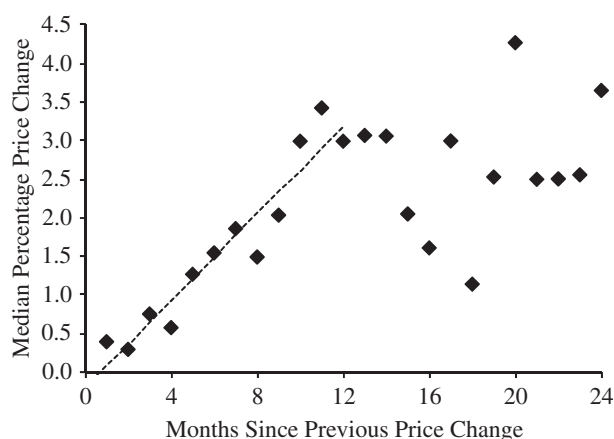


Fig. 11. *Median Percentage Price Change and Number of Months Since Previous Price Change*

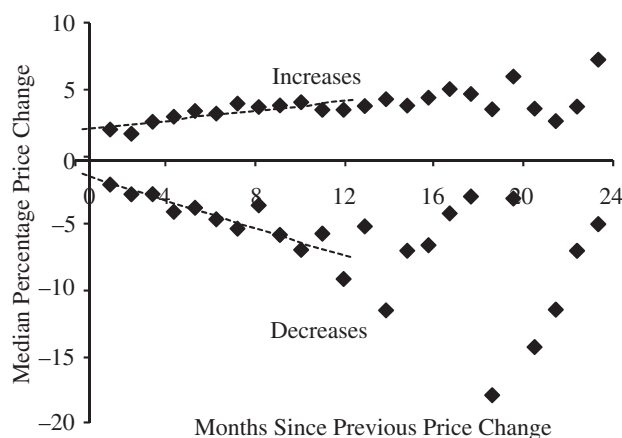


Fig. 12. *Median Percentage Price Rise or Fall and Number of Months Since Previous Price Change*

we get towards two years, as relatively few prices in the data set are unchanged for more than 18 months.

Separating the analysis into price increases and price decreases (Figure 12), price increases are larger for price changes that are infrequent, and price decreases are also larger (or more negative) where the duration since the previous price change is longer. Again these relationships are reasonably good where prices change within one year of the previous change (the best-fit lines are shown as the dotted lines in the Figures 11 and 12), but they are less robust beyond one year. The best-fit line for price decreases has a slightly steeper slope than the line for price increases – which could indicate some potential non-linearity in price adjustment. That could be consistent with firms being more able to pass on price cuts than recover rises in costs through higher prices.¹⁰

6. Implications for Pricing Theory

One of the key motivations for analysing micro-price data is to understand more about how prices are set, and in particular about the degree of nominal rigidity in the economy. Nominal rigidities imply that prices cannot be freely adjusted but they can take a number of different forms in monetary policy models. Depending on the assumptions made about the structure of these rigidities, different models can have very different policy implications.

In the data, UK producer prices do not adjust continually – we find that only a quarter of prices change in any given month and price changes occur less frequently when measured by the average duration for individual products, reflecting the heterogeneity in the data. Some firms may review their price each month and decide not to change it; nevertheless three-quarters of firms not changing price each month would be consistent with the presence of some type of nominal rigidity in product markets.

The empirical evidence presented is not clearly supportive of any one pricing theory. There are pieces of evidence that both support and detract from different models. For example, the strict price-setting model proposed by Calvo (1983), which implies a constant probability of price changes in each period, is not consistent with the variation in the share of prices changing that we see in different years and in different calendar months of the year. It is also not consistent with the spikes that we observe in the hazard functions, which show that the probability of a price changing varies depending on the duration since the previous price change. However, the hazard functions are relatively flat apart from the spikes at 1, 4 and 12 months and could still be consistent with other time-dependent type models such as staggered contracts (Taylor, 1980); it is possible that downward sloping hazard functions could be a result of aggregating across heterogeneous price-setters (Álvarez *et al.*, 2005).

If models with small fixed costs of price adjustment were able to explain the nominal rigidities we see in the data fully (Mankiw, 1985), we might expect to see relatively few small price changes in the data. But we find that almost half of all price changes are between -2% and $+2\%$, which we might regard as small. Such adjustment costs may still

¹⁰ The best-fit lines in Figure 12 do not go through the origin and nor should we expect them to. The fact that the best-fit line in Figure 11 almost goes through zero is by chance rather by construction.

be important for the other half of price changes that are larger, or it could be that menu costs and pricing behaviour are heterogeneous, for instance with some sectors having very small costs of adjustment but other sectors facing much larger costs. But a single aggregate 'menu costs' pricing model that attempts to explain why prices change (without heterogeneity) is not consistent with our results.

Similarly, a quadratic adjustment cost model, as set out in Rotemberg (1982), also fails to match the data. Rotemberg's model, where firms minimise deviations from their optimal price subject to (quadratic) costs of changing output, suggests that firms adjust prices continuously – prices move slowly from their previous level to the new optimal level. Our analysis rejects this result – we do find evidence of infrequent price adjustment and we find that there are a number of large price changes in the data that are not consistent with gradual adjustment towards an optimal price. And, as with other theoretical models, by itself a single Rotemberg model cannot account for the observed heterogeneity in the frequency of price adjustment.

The heterogeneity that we find in pricing behaviour across different industries and product groups is perhaps the most interesting result from our study, and chimes with similar observations from other microdata studies. Given this heterogeneity, it is likely that particular theories can better explain pricing behaviour in some sectors than in others and therefore it may be difficult to find any one theory that can explain pricing behaviour at the economy-wide level. For example, almost 90% of energy product prices change each month and, therefore, it could be argued that nominal rigidities are not particularly important in this sector. But less than 10% of clothing products change price each month, and therefore a different model may be needed to explain the nominal rigidities in this sector. This heterogeneity would argue against the use of 'representative agent' type models.

The finding that no one theory can explain how firms set their prices is consistent with the recent Bank of England price-setting survey (Greenslade and Parker, 2010). The survey found that some UK firms use mainly time-dependent pricing rules (44%), some use state-dependent pricing rules (15%) and the remainder use a combination of the two. The heterogeneity in pricing behaviour across different sectors is also clear in the results of the pricing survey.

7. Conclusion

This article has examined pricing behaviour at the individual item level for manufacturing companies in the UK. In doing so, we have added to the growing literature of micro-pricing studies, providing the first set of recent UK results using data underlying official inflation statistics.

Using the data that underpins the UK Producer Prices Index, we have uncovered several interesting features about the behaviour of those prices. First, on average 26% of producer prices change each month, although there is considerable heterogeneity between sectors and product groups. This is similar to our findings for UK consumer goods (Bunn and Ellis, 2011). A small number of items account for many price changes, which implies that price changes are less frequent when measured by the average for individual products: the median number of months between price changes per item is seven. Second, the probability of price changes is not constant over time:

prices are most likely to change 1, 4 and 12 months after they were previously set. Third, the distribution of price changes is wide, although a large number of changes are relatively small and close to zero. Fourth, prices that change more frequently tend to do so by less.

These results suggest that none of the conventional theories for price stickiness is clearly borne out by the data. In particular, the marked degree of heterogeneity in the behaviour of prices is often just ignored, for example in the typical ‘representative agent’ models. These results imply that, if we really want to understand and model prices with any degree of accuracy, we need to find a way of capturing the richness of the heterogeneity that is present in the data. One option here could be to further pursue the so-called ‘factor augmented vector autoregression’ models set out by Boivin *et al.* (2007) and Mumtaz *et al.* (2009). An alternative avenue would be to explore some of the dynamic programming analysis (Miranda and Fackler, 2004) that is typically more prevalent in other fields, such as consumption theory. But, whatever direction future work takes, if we want to use genuinely micro-founded models – that is, models that match the heterogeneity in the microdata – we need to improve the pricing models that are currently employed.

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EXAMINING THE BEHAVIOUR OF INDIVIDUAL UK CONSUMER PRICES*

Philip Bunn and Colin Ellis

This article examines how UK consumer prices behave, using two databases with millions of price observations: the microdata that underpin official Consumer Prices Index data and a database of supermarket prices. Prices do not change continuously but our key finding is the marked heterogeneity in the data. That is not consistent with standard microeconomic foundations that typically form the basis of macroeconomic policy models. Declining hazard functions and the distribution of price changes also argue against representative agent models. Our results suggest further work is needed to find a model of price-setting that genuinely corresponds to how individual UK consumer prices behave.

Many central banks around the world have adopted some form of inflation target on which their monetary policy actions are based. Typically, that target is defined in terms of an aggregate price index, such as the Consumer Prices Index (CPI) in the UK. Given that this aggregate price index is a weighted sum of individual prices, changes in those individual prices will have important implications for both the overall price level and for relative prices within the aggregate. So, learning more about how often individual prices change and how much they change by is essential for monetary policy makers.

Prices are typically thought to be sticky, or slow to adjust, because of the presence of some type of constraint, often referred to as nominal rigidities, which imply that prices cannot adjust instantaneously or costlessly. Economic models typically include some type of mechanism to incorporate these nominal rigidities. A number of different mechanisms have been proposed. These can be categorised under two main headings: time-dependent and state-dependent pricing.

In a time-dependent model, the probability of a price change can only be affected by the time since the previous change, and it is not influenced by the state of the firm's sales, the economy or other factors. In the simplest form of model proposed by Calvo (1983), homogeneous firms actually have a fixed probability of changing their price in each period (i.e. the probability of a price change does not depend on when the previous change occurred). Alternative time-dependent models include staggered contracts in which prices are fixed for the duration of a contract and contracts overlap in that they do not all start and end at the same time (Taylor, 1980). In a

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The views expressed in this article are those of the authors, and not necessarily those of the Bank of England, the University of Birmingham or the BVCA. We thank the Office for National Statistics (ONS) for making the data available to us. We are also grateful to Neal Hatch, Steve Millard, Nick Oulton seminar participants at the Bank of England an anonymous referee for the Bank of England working paper series, two anonymous referees for this Feature and Steve Machin for useful comments. This work contains statistical data from ONS which is Crown copyright and reproduced with the permission of the controller of HMSO and Queen's Printer for Scotland. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

state-dependent model, the decision to change prices depends on the state of the economy and the market faced by the firm. Firms are typically assumed to face a cost to adjust their price. Examples of these costs include fixed costs of changing price – so-called menu costs (Mankiw, 1985) – or a disutility associated with making large price changes if firms fear that making such changes may upset their customers (Rotemberg, 1982). Examining how actual prices behave may help to shed light on which of these theoretical models are more relevant to the real world.

There have been a number of international studies that have used large databases of individual price quotes to examine how consumer prices behave at the micro level, in particular Bils and Klenow (2004) and Nakamura and Steinsson (2008) for the US, and Dhyne *et al.* (2006) for the euro area. However, no work has been done regarding the empirical examination of individual UK consumer prices by using a large database of actual price quotes. This article addresses that gap, using two different data sources to analyse how individual consumer prices typically behave, and considers what the results of this analysis imply for the mechanisms that underlie nominal rigidities in the UK economy. A companion article (Bunn and Ellis, 2011*b*) provides a detailed examination of UK producer prices.

This article is organised as follows. Section 1 describes the two data sources used, and compares and contrasts the differences between them. Section 2 deals with the frequency of price changes that we observe from the two datasets and the impact of temporary promotions or sales on the frequency of price changes. It also covers how the frequency of price changes has varied over time and the size of price changes. Section 3 discusses the hazard functions that are implied by the underlying data. Section 4 discusses the potential implications of these findings for theories of nominal rigidity and UK policymakers, and Section 5 concludes.

1. The Underlying Data

In order to examine the behaviour of individual consumer prices at the microeconomic level, rather than the macroeconomic one, we first needed to source the data. Previous studies for other countries have typically either focused on the individual price quotes that underlie official inflation data (Bils and Klenow, 2004; Dhyne *et al.*, 2006), or instead have considered individual price information based on so-called scanner data from supermarkets (Chevalier *et al.*, 2000; Kehoe and Midrigan, 2007). Both sources have their advantages and disadvantages, in terms of timeliness, frequency and accuracy. For this article, we combine results from both types of data.

Our official microdata are taken from the price quotes that underpin the monthly UK CPI and Retail Prices Index (RPI) data releases. On the second or third Tuesday of every month, the Office for National Statistics (ONS) collects data on the prices of individual consumer goods and services. These raw price quotes are then weighted together and aggregated to form the monthly CPI and RPI indices.¹ Along with data from other statistical releases, ONS makes the microdata underlying the CPI and RPI

¹ The CPI is a harmonised measure of consumer prices that is internationally comparable with other European Union member states' indices. But important differences between indices remain, such as different weights and different composition of the inflation baskets.

available to researchers via its secure Virtual Microdata Laboratory (VML), described in Ritchie (2008). The analysis of official consumer price data presented in this article was conducted within the VML, giving unprecedented access to individual UK consumer price observations – overall, our analysis included over 11 million price quotes recorded between 1996 and 2006, covering 600,000 different products. The same individual items are not present in all periods since the sample is regularly updated to ensure it remains representative. Only the locally collected data that make up the CPI – where ONS price collectors go into shops and record selling prices – were available. A set of centrally collected data – where the ONS collects national prices from particular companies – were not readily available. The locally-collected data make up around two-thirds of the aggregate CPI by weight, and are relatively sparse for the communication sector compared with the aggregate weights in the CPI (Figure 1).²

The examination of these price quotes underlying official inflation data is very useful. However, they are only available on a monthly frequency. In addition, therefore, this article also considers weekly supermarket price data that were supplied by Nielsen, the research consultancy. This analysis examines prices recorded at the point of sale – i.e. scanner-level data from supermarket till receipts. While these data may be less comprehensive than price data compiled by national statistical offices, in that they will not cover the entire range of households' consumption decisions, the higher frequency of observation allows us to examine the behaviour of (particular) individual prices more closely. Because the prices that are used to calculate inflation indices are typically collected on one day in any given month, they therefore give no indication about what happens to prices within each month, between the collection dates. If prices change from week to week, this volatility will be automatically removed from the monthly data – as, by definition, the most these price observations can exhibit change is once a month.

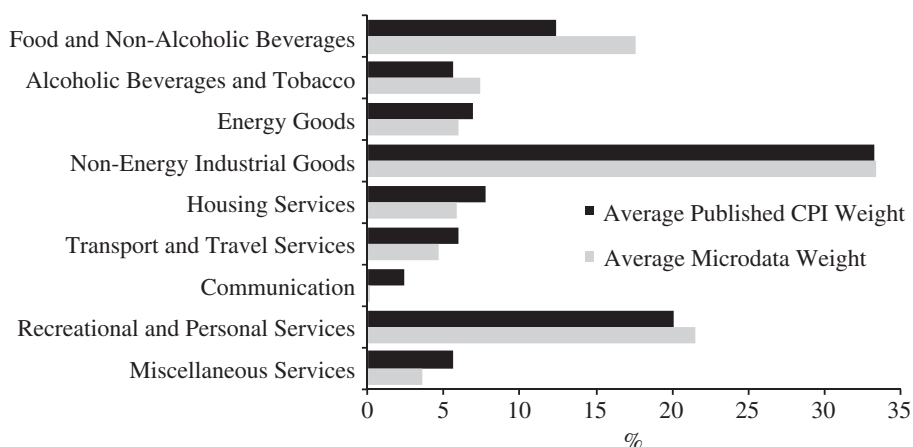


Fig. 1. *Weights by Consumer Price Index (CPI) Component*

Sources. ONS and CPI microdata.

² Further details on the CPI microdata are available in Bunn and Ellis (2011a). When we tested the impact of these different weights on our results, our findings were broadly unaffected, suggesting that the weighting difference did not have a significant impact.

The weekly supermarket scanner data included around 230 different supermarkets located throughout Great Britain, covering the largest retailers. Just over 280 distinct products were included in the dataset, but as not all stores stock all products, some products appear intermittently. The individual products were chosen both with consideration to data availability, and to try to get a broad range of different types of goods. In all, the dataset covered 3 years of sales, from February 2005 to February 2008, and a total of 5½ million individual price quotes, or roughly 35,000 different price observations each week. One important point is that the data provided were average selling prices for each week. This means that temporary changes in prices, such as special promotions or selling damaged goods more cheaply, will affect the observed price. This was particularly an issue for the ‘fresh’ product category, which was by far the largest grouping by sales volume, and the least differentiated. As such, it is unlikely to be representative of the other categories in the supermarket data. Overall, total sales in the scanner data accounted for just under 5% of total UK household expenditure over the sample period. Table 1 provides a breakdown of the supermarket data by product category.³

2. The Observed Frequency of Price Changes and the Impact of Temporary Promotions

One key focus of our analysis is to examine the frequency with which individual prices change, and compare and contrast our observations with the assumptions or implications of macroeconomic models. In doing so, the treatment of temporary promotions is an important consideration.

While temporary promotions, or sales, are an important indicator of price flexibility – their incidence demonstrates that firms can change prices easily and swiftly, suggesting that menu costs are low – their implications on a macroeconomic scale may

Table 1
Supermarket Sales by Product Category

Category	Number of price quotes		Sales values	
	Number	Percentage of total	£ million	Percentage of total
Alcohol	319,195	5.6	6,449	5.9
Bakery	161,087	2.8	1,624	1.5
Confectionary	544,268	9.6	2,138	2
Dairy	614,746	10.8	12,778	11.7
Fresh	1,030,831	18.1	61,890	56.7
Frozen	255,294	4.5	1,986	1.8
Grocery	1,234,536	21.7	10,323	9.5
Household	408,352	7.2	3,430	3.1
Personal	492,449	8.7	2,560	2.3
Soft drinks	621,778	10.9	6,033	5.5
Total	5,682,536	100	109,110	100

Source. Nielsen microdata.

³ Further detail on the supermarket scanner data is available in Ellis (2009).

be limited. These sorts of short-term fluctuations are perhaps more likely to reflect cashflow or stock management considerations on the part of producers or retailers, rather than underlying macroeconomic conditions, and as such there is a case for smoothing through some of the volatility that temporary promotions cause, in an effort to focus on underlying pricing behaviour.

This implies that we need some mechanism for identifying and excluding temporary promotions in our two datasets. As part of the data collection process, ONS price collectors indicate whether a particular price in any given month is temporarily discounted or not, providing us with a ready-made indicator. This was not available for the scanner data, and therefore an alternative metric was required.

Previous work in this area suggested two mechanisms for excluding the impact of temporary price changes. The first is the notion of the so-called ‘reference price’ suggested by Eichenbaum *et al.* (2008). This ‘reference price’ is simply the modal price within any given calendar quarter, and hence abstracts from any variation in the data within each quarter. The second mechanism was taken from Kehoe and Midrigan (2007), who use a notional ‘regular price’. Under this method, price reductions are classified as temporary promotions if they are reversed sufficiently swiftly, in this instance within 5 weeks. In that sense, the ‘regular price’ concept has similarities to the ‘reference price’, in that both are defined in part by the length of the window of observation, and are hence dependent on the (subjective) length of that window. So we also considered ‘price reversals’ – where, following a rise or fall in any given price, the subsequent move is an exact reversal. Unlike regular and reference prices, these price reversals were not time-bound, thereby offering an alternative means of abstracting from both temporary price reductions and temporary price hikes.

2.1. *Comparing Price Changes Between the Two Datasets*

The CPI microdata provided by the ONS contain identifiers that classify an individual price quote according to its exact product type and the location in which the price was collected. Using these identifiers, a time series of price quotes for each individual item (defined as a specific product in a specific location) was constructed. This was then used to identify whether a price change occurred for each item in a particular month of the data. The results were aggregated across the sample and each individual price quote was weighted to calculate an average figure for how many prices changed in that month.

In the CPI microdata, weighting ensured that the results were not biased towards products where the ONS collects larger samples of price quotes. The ONS collects larger samples of price quotes for some groups of products where it believes that it is necessary to produce a reliable estimate of the average price, for example where there is a lot of diversity within a product group. The individual CPI price quotes were weighted according to the weight of that individual item within the locally collected component of the CPI in the relevant year; these weights are based on expenditure shares.

Similar techniques were used to estimate how often supermarket prices change as were used for the CPI microdata. In the supermarket scanner data, each individual supermarket price quote was weighted according to the sales (i.e. the spending share) of that product over the 3-year data sample.

Table 2
Frequency of Consumer Price Changes

Price measure	Sample	Percentage of prices changing	Implied duration between price changes
Monthly Consumer Price Index (CPI) microdata	1996–2006	19% a month	5.3 months
CPI goods	1996–2006	24% a month	4.2 months
CPI services	1996–2006	9% a month	11.1 months
CPI excluding promotions	1996–2006	15% a month	6.7 months
Weekly supermarket data	February 2005–February 2008	60% a week	1.7 weeks
Excluding fresh products	February 2005–February 2008	40% a week	2.5 weeks
Excluding fresh products and price reversals	February 2005–February 2008	27% a week	3.7 weeks

Notes. Monthly CPI microdata are locally-collected data only. All figures are weighted by sales values.

Sources. CPI and Nielsen microdata.

Table 2 summarises how often prices change in the CPI and supermarket data. All the results presented in this article are presented on this weighted basis.⁴ On average, 19% of CPI prices change each month. This implies an average duration between price changes of approximately 5 months. According to ONS price collectors, around 7% of the price quotes in the UK consumer price data are identified as either being temporarily discounted sale prices or prices recovering from a sale in the previous month. Excluding these observations that relate to promotions, the proportion of consumer prices changing each month falls to 15%. The results suggest that UK consumer prices change slightly more often than in the euro area, where 15% of prices were found to change each month (Dhyne *et al.*, 2006). In part this could reflect different sample periods and weightings. Dhyne *et al.* (2006) only report results based on a sub-sample of 50 products, whereas we use all items in the UK CPI whose prices are collected locally. Differences in sample period appear unlikely to account for much of the difference: restricting our sample to the same 1996–2001 time period used by Dhyne *et al.* (2006), the share of UK consumer prices changing each month is still 19%. UK consumer prices appear to change less often than in the US, where around 26% of prices are estimated to change each month (Bils and Klenow, 2004).

In contrast, weekly supermarket prices appear to change much more frequently than is implied from analysing the prices used in the construction of the CPI. The UK data suggest that, excluding fresh products, about 40% of prices change each week, or the average duration of prices is around two and a half weeks. Total sales were heavily weighted to fresh products (57% of the sample), whose prices change very frequently, so excluding these products may give a better read on underlying price flexibility. This is a lower duration than the CPI retail goods data, and there are a number of possible explanations for this result.

The first is that the weekly supermarket data are picking up large numbers of temporary promotions that are not captured in the monthly CPI data. Excluding all price changes that are direct reversals of the previous change – a proxy for temporary

⁴ For more detail on the weighting, and the technical construction of results in this article, see Bunn and Ellis (2011a) and Ellis (2009).

promotions – the share of prices changing each week (excluding fresh products) falls to 27%, or an implied price duration of just under a month.⁵ Second, the supermarket sample is predominately food items and other goods, and food products within the CPI sample change price slightly more frequently than the average for all products (as discussed in Section 2.2). Third, the coverage of the CPI data is very different from our supermarket data: the former cover prices from a much wider range of shops than just large supermarkets and price-setting behaviour may not be the same among all types of retailers. Arguably, we should not expect the two data sources to deliver the same results.

The fact that we observe supermarket prices changing very frequently is also consistent with US evidence from Kehoe and Midrigan (2007), who found that 33% of supermarket prices changed each week. Nevertheless, the high levels of flexibility observed in the weekly scanner data could suggest that UK prices may in reality change more often than in the monthly ONS microdata because, by construction, the most prices can change in the ONS micro dataset is once a month. In order to examine how the frequency of price collection can affect resulting estimates of price duration, we constructed reference prices based on the supermarket scanner data, to see if abstracting from high-frequency movements in prices could yield misleading inferences about price flexibility. Reference prices were constructed at monthly and quarterly frequencies, and results are shown in Table 3.⁶

Our analysis indicates that, using monthly reference prices, 44% of prices changed each month (excluding fresh products), implying an average price duration of just over 2 months. That compares with a duration of around a month if we use price reversals or regular prices to control for temporary promotions (Table 2), suggesting that reference prices yield misleading inferences about the underlying frequency of price changes. The impact is correspondingly larger when we construct quarterly reference prices, which imply an average price duration of around 6 months. The clear implication here is that high-frequency data do offer a far richer picture of pricing behaviour in the UK, and simply relying on monthly or quarterly averages can be misleading. Even if we want to isolate the impact of temporary sales on price fluctuations, the precise manner of this control is very important. While the implied price duration of 2 months

Table 3
Frequency of Changes in Supermarket Reference Prices

Reference prices changing each period	%
Quarterly reference prices	
Total	68.7
Excluding Fresh	50.3
Monthly reference prices	
Total	64.0
Excluding Fresh	44.0

Source. Nielsen microdata.

⁵ This result was broadly the same when we focused on regular prices following Kehoe and Midrigan (2007), instead of excluding price reversals.

⁶ Where there were multiple modes within the reference window, we used the maximum mode within each period, on the basis that most temporary promotions involved price cuts.

for supermarket data (using monthly reference prices) is closer to the observed frequency of price change for goods products in the CPI data (Table 2), it is still significantly higher than CPI data suggest. In part, this is likely to reflect the different samples and coverage of the two data samples: the CPI data cover a much wider range of products and shops, while large retailers such as supermarkets may change prices more frequently than smaller retailers. As such, we must be careful to bear these caveats in mind when comparing results from the two datasets.

However, our data are generally consistent with these promotions being temporary in nature, in line with international studies. In the CPI microdata, 67% of 'sale' prices change each month, consistent with most promotions lasting less than 8 weeks. Furthermore, the average duration of a price reversal in the scanner data was between 2 and 3 weeks, consistent both with the observed duration of promotions when gauged using 'regular prices' and Kehoe and Midrigan's (2007) earlier findings in the US. These promotions do genuinely appear to be short-lived and, while still an indicator of overall nominal rigidity, may not directly be related to underlying macroeconomic conditions or policy.

2.2. Price Changes Across Sectors and Product Groups

Consumer goods prices change more often than the prices of services, an average of 24% of goods prices change each month compared to only 9% for services. But there are also differences in how often prices change within these categories (Figure 2). In particular, there is marked heterogeneity in the behaviour of prices among the different goods components. The prices of energy items, predominately petrol in the locally-collected CPI microdata, change the most frequently.⁷ This probably reflects

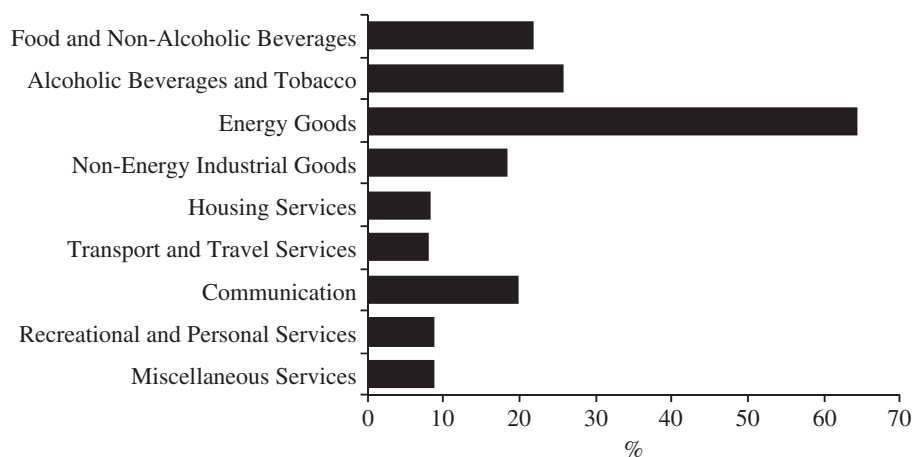


Fig. 2. *Percentage of UK Consumer Prices That Change Each Month*

Note. Including temporary promotions.

Source. CPI microdata.

⁷ Domestic gas and electricity prices data used to construct the CPI are collected centrally by the ONS and are therefore excluded from the locally-collected microdata that we had access to.

the relatively swift pass-through of changes in oil prices from global commodity markets to petrol prices. It also implies that, given that other consumer prices do not adjust as frequently, relative price effects can impact the headline CPI inflation rate over the short to medium term. Among other goods components, the prices of non-energy industrial goods change less frequently than the prices of food, beverages and tobacco. Sales appear particularly prevalent in the prices of non-energy industrial goods: around half of all changes in the prices of these goods are accounted for by sales and recoveries from sales.

Across the CPI microdata as a whole, 45% of the changes in goods price changes are falls, while only 20% of the changes in services prices are falls. These results were broadly comparable with findings for the euro area (Dhyne *et al.*, 2006). The fact that service prices are less likely to fall than goods prices in our sample is consistent with the observation that service price inflation (which averaged around 4%) was higher than goods price inflation (which was close to zero on average) over our sample period, and also that goods are much more likely to be in the sale (which would involve price cuts) than service prices.

We also observed considerably less heterogeneity between the five services components of the CPI than was evident within the goods components. Four of the services components exhibited an average frequency of price change of between 8% and 9% per month. The exception was communication services, where prices changed more frequently, although unfortunately our data sample was relatively limited here. Over 60% of changes in communication services prices were falls, consistent with persistent negative inflation for this component during our sample period.

Despite coming from a subset of the overall CPI basket, this marked heterogeneity between different product categories was also evident in the supermarket scanner data (Figure 3). In the supermarket data the prices of fresh products (which also have the largest weight) change the most often, followed by alcohol and soft drinks. However,

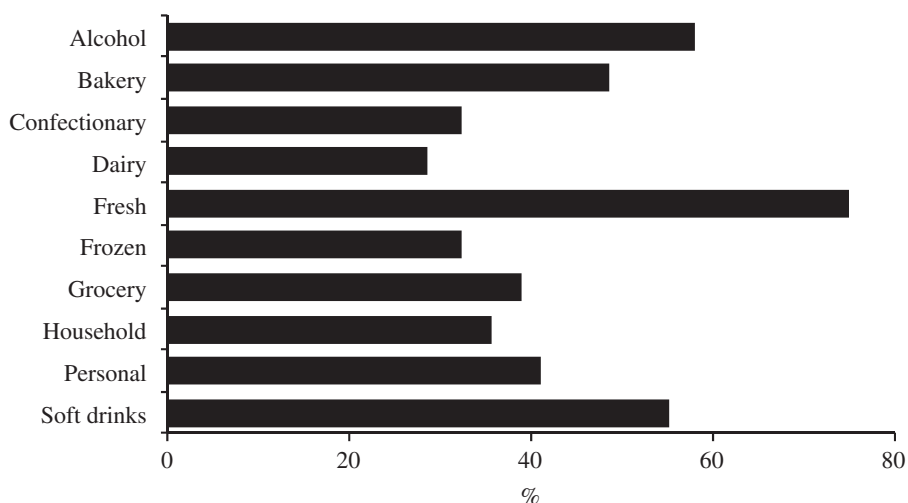


Fig. 3. *Percentage of UK Supermarket Prices That Change Each Week*

Source. Nielsen microdata.

across all categories the incidence of price changes was broadly split between price falls and price rises, indicating that downward nominal rigidities – constraints which prevent firms from reducing prices – were not a strong feature of supermarket data. This result also held after stripping out temporary promotions. The high incidence of price changes in the fresh goods and bakery categories, in particular, is consistent with the relatively short shelf-life of these types of products. However, the observed frequency of price changes for alcohol and soft drinks was also high, which is more likely to reflect competition or stock management.

2.3. Does the Probability of Price Changes Vary Over Time?

It is interesting to look at how the likelihood of price changes varies over time to give some idea as to how sensitive the results are to the time period used and to help shed light on whether time-dependent pricing models provide a good explanation of how prices are set. In its simplest form, a time-dependent pricing model implies the probability of a price change is the same in each period. There are two ways to explore the predictions of this model in the data. The first is to look at the frequency of price changes in different periods. The second is to plot hazard functions for our microdata, which are discussed later.

The average share of CPI consumer prices changing each month varies between 16% and 22% in different years of the sample. In the CPI microdata there is some evidence of a correlation between the average share of prices increasing each month and the aggregate inflation rate that these data underlie (Figure 4): the correlation coefficient between these two series is 0.6. However, there is less sign of a relationship between inflation and the share of prices decreasing. The share of supermarket prices changing each week also varies over time but that dataset also covers a shorter time period than the CPI microdata. This variation in the frequency of price changes

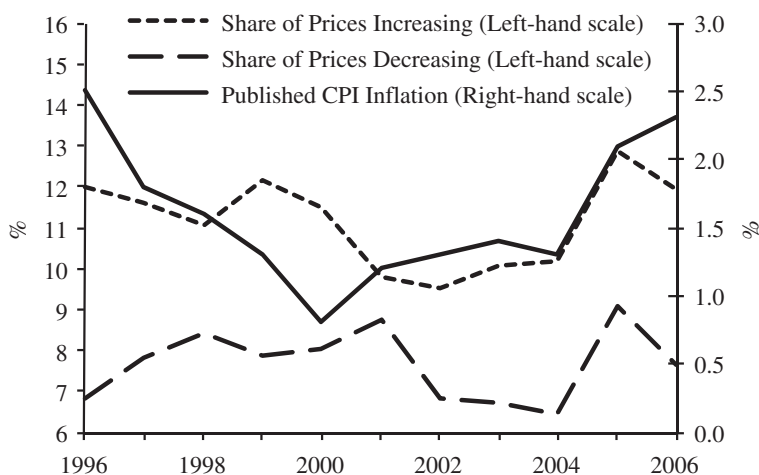


Fig. 4. Headline Inflation and Percentage of Consumer Price Index (CPI) Prices Changing Each Month

Sources. ONS and CPI microdata.

over time is not consistent with the predictions of a strict time-dependent pricing model.

Over a period where inflation rates have been positive, it is not surprising that we observe more price increases than decreases in our data. However, both datasets exhibit a significant proportion of price cuts: around 40% of all CPI price changes were decreases, while price falls accounted for half of all price changes in the supermarket data. Excluding the effects of temporary sales, approximately 35% of all consumer price changes were still price cuts. The large share of price changes that are price falls suggest that downward nominal rigidities are not a major factor in UK product markets.

In addition, we observe the well-known seasonal variation in prices in the microdata. More consumer prices change in January than in any other month of the year, as firms reduce prices as part of the January sales (Table 4). Excluding all sale prices, consumer prices are most likely to change in April. That could reflect changes in duties and/or firms changing prices to coincide with the start of a new financial year.

2.4. *The Magnitude of Consumer Price Changes*

In addition to the frequency of price changes, our data also allow us to examine the size of individual consumer price changes in the UK economy. This can test the assumptions of some state-dependent pricing theories. If few small price changes are observed in the data that might suggest that fixed costs of price adjustment (menu costs) are important. In contrast, if firms face significant disutilities from making large price changes that would suggest the majority of price changes should be small. Studying the distribution of price changes may help to shed light on the extent of downward nominal rigidities in product markets. The existence of such rigidities would be consistent with there being few falls in prices, particularly small falls.

Across both datasets the median price change is an increase of between 0% and 2%, but in both instances the distribution of the size of price changes around the central estimates is wide with a number of large price changes. Compared with the aggregate

Table 4
Frequency of Consumer Price Index (CPI) Price Changes by Month

Month	Price changes (%)	Price changes excluding promotions (%)
January	22.1	16.6
February	18.1	14.8
March	18.7	16.0
April	21.2	18.1
May	19.5	16.6
June	19.8	16.7
July	20.1	15.3
August	18.1	14.6
September	17.1	13.8
October	17.9	14.4
November	16.8	13.4
December	16.8	13.6

Source. CPI microdata.

CPI inflation rate, which was always between 1% and 3% over our sample period, individual price changes can be much larger than the headline data might suggest. Figure 5 plots the distribution of price changes in our data, splitting the CPI microdata into goods and services prices, given the difference that we observed in the frequency of price changes. Table 5 summarises the quartiles of the distribution. There are also a significant number of price changes that are relatively small and close to zero. Around 20% of price changes in the overall CPI data are between -2% and 2% .

Once again there are differences between the behaviour of consumer goods and services prices: there have tended to be more increases and fewer decreases in services prices than in goods prices. These differences are also evident at a more disaggregated

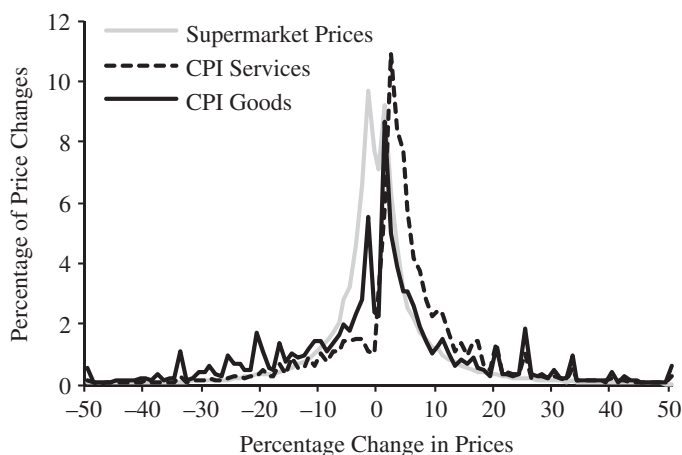


Fig. 5. *Distributions of the Magnitude of Price Changes*

Note. Samples include temporary promotions.

Sources. CPI and Nielsen microdata.

Table 5

Distributions of the Magnitude of Price Changes (Percentage Changes)

	25th percentile	Median	75th percentile
All supermarket items	-3.2	0.2	3.5
All Consumer Price Index (CPI) items	-6.3	1.7	8.3
CPI goods	-7.9	1.3	7.8
CPI services	1.1	4.0	9.3
CPI food and non-alcoholic beverages	-11.2	2.6	12.7
CPI alcoholic beverages and Tobacco	-0.9	1.5	4.7
CPI energy goods	-1.5	1.3	3.1
CPI non-energy industrial goods	-17.9	-0.1	17.6
CPI housing services	-4.8	5.0	11.8
CPI transport and travel services	0.9	6.7	15.3
CPI communication	-16.7	-8.3	11.1
CPI recreational and personal services	1.3	3.4	7.3
CPI miscellaneous services	2.5	5.5	11.4

Note. Samples include temporary promotions.

Sources. CPI and Nielsen microdata.

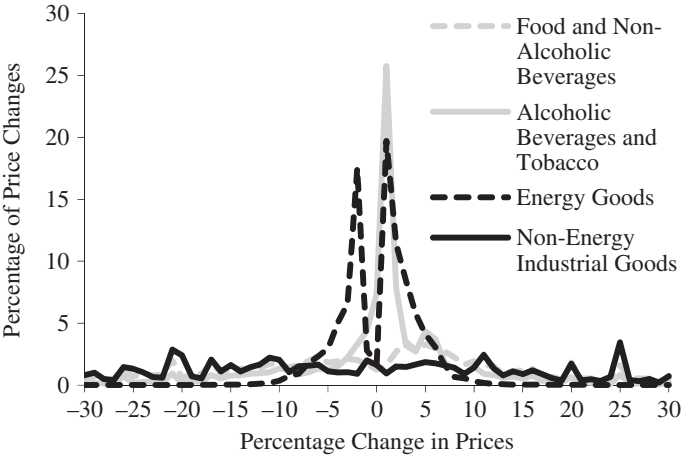


Fig. 6. *Distribution of Consumer Goods Price Changes*

Note. Sample includes temporary promotions.
Source. CPI microdata.

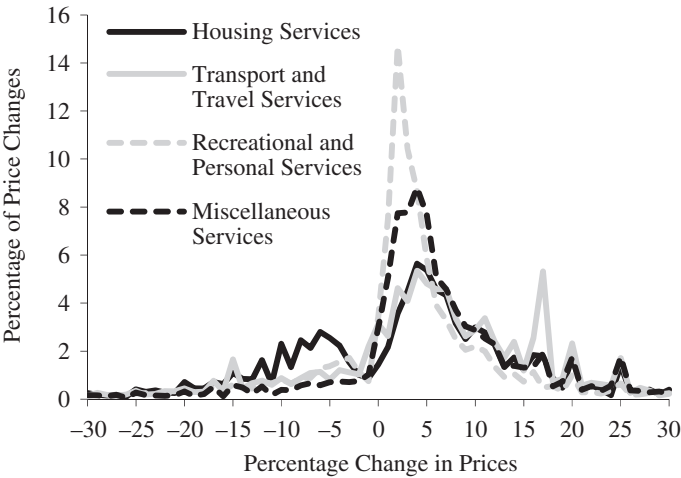


Fig. 7. *Distribution of Consumer Services Price Changes*

Note. Sample includes temporary promotions.
Source. CPI microdata.

component level (Table 5, Figures 6 and 7). Among the goods components, a large proportion of changes in the price of energy goods and alcoholic beverages and tobacco are relatively small. The interquartile range of the size of price changes for those components is relatively narrow at around 5% points. For alcohol and tobacco, these changes are more likely to be increases, and are particularly concentrated between 1% and 2%, which in part may be associated with changes in duty on those products. Among energy goods, which is dominated by petrol, relatively few price changes are between -1% and 1% , but a large proportion lie between -1% and -2%

and 1% and 2%. This is probably because petrol prices typically change in units of one pence per litre, which over our sample period implies a price change of between 1% and 2%. In contrast, the distributions of price changes for food and non-alcoholic drinks and non-energy industrial goods look very different, with a wide interquartile range of 35% points, little or no peak around zero and wider tails. This implies that the shape of the aggregate distribution of goods price changes, which has some large changes and some concentration in small price changes, results from the aggregation of these two different types of distribution at the component level. Once again, this illustrates the heterogeneity in price-setting behaviour that is evident in the data.

With the exception of communications, there was rather less heterogeneity between the distributions of price changes in consumer services. Across the four other broad services sectors, all exhibited some concentration of price changes between 0% and 10%, as well as a relatively small proportion of price reductions. Recreational and personal services had the largest proportion of small price changes and therefore the narrowest interquartile range among the services components. The spike of price changes of between 2% and 3% for this component accounted for most of the corresponding spike in the overall service price distribution.

The distribution of the size of supermarket price changes looks broadly similar to the distribution of the size of consumer goods price changes (Figure 5). However, there is a higher proportion of smaller price changes in the supermarket data and therefore a smaller difference between the upper and lower quartiles of the distribution (Table 5). This suggests that large numbers of temporary promotions – where price changes are likely to be relatively large – cannot fully explain why weekly supermarket prices appear to change so much more frequently than prices of the items which make up the CPI. It could also reflect using average prices in the supermarket data where short-term price reductions, for example to sell off stock approaching its sell-by date, could explain some of the small changes in supermarket prices, especially among fresh products which make up a significant proportion of the sample.

State dependent pricing models typically assume that firms face a cost to adjust their prices, or face a disutility associated with making large price changes. The large number of relatively small price changes that occur in all datasets suggests that small fixed costs of price adjustment may not be important for many firms. In addition, however, the significant number of large price changes that are present in the data are not consistent with those firms receiving disutility from making large price changes. As such, the evidence from our microdata suggests that a single state-dependent pricing model may not be able to explain price-setting behaviour in the majority of firms.

2.5. The Relationship Between the Frequency and Magnitude of Consumer Price Changes

From our previous results, we have observed a wide distribution of price changes, as well as relatively frequent price changes overall. One hypothesis that the microdata allow us to explore is whether there is a link between the frequency and magnitude of price changes – i.e. the longer it has been since the last price change, the more price-setters change their prices by when they next move them. For instance, if firms face some constraint that encourages them to set prices at infrequent intervals, then there is

more scope for the actual price to differ from the optimal price as more time passes since the last price change.

We can examine this by plotting the duration of a price since its previous change against the size of that price change. Across the whole distribution of CPI microdata, there appears to be a clear positive relationship between the frequency and duration of price changes. The median price change, when that change occurs within 3 months of the previous price change, is an increase of just over 1%. In contrast, if a year has passed since the last price change then the median price change is roughly 3%, and at 2 years since the last price change this rises to around 5%.

When we split price changes into increases and decreases, we also find evidence of a relationship between frequency and magnitude. However, while there is a positive correlation between the two for price increases, as across the entire dataset as a whole, there is also a negative correlation between duration and magnitude for price cuts – the longer it has been since a previous change in prices, the steeper the price cut we observe in the data (Figure 8).

In light of this result, is it not surprising that the link between the frequency and magnitude of price changes is strongest for consumer services prices as opposed to goods prices, as relatively few changes in services prices are decreases and the incidence of temporary promotions is much smaller. In fact, the correlation between the median price change and the number of months since the previous change is around 0.95 for consumer services prices. In contrast, the correlation between frequency and magnitude for consumer goods prices is much less clear in the raw microdata, reflecting the impact of sales. Once these sale prices are excluded, a far stronger relationship is evident, with a positive correlation of 0.85 between the size of and time between changes in goods prices. However, we did not observe a significant relationship between the magnitude and frequency of price changes in the scanner data. This probably reflects the fact that, even excluding fresh produce and sales, the average

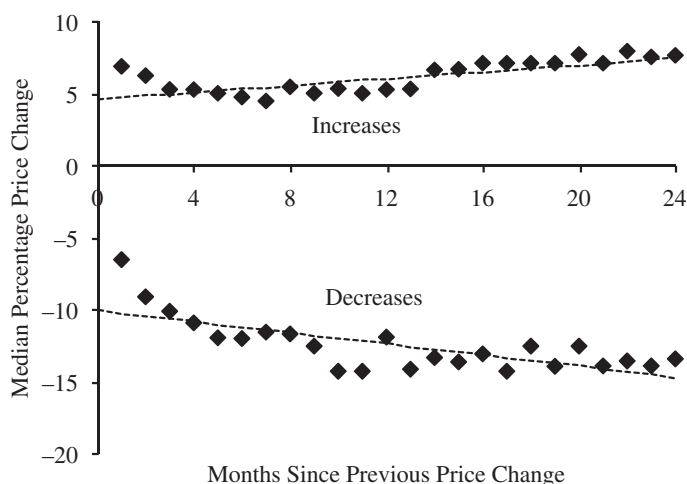


Fig. 8. *The Magnitude and Duration of Price Rises and Cuts*

Source. CPI microdata.

price duration was only a month and there were very few products whose price was unchanged for a long period of time.

3. Hazard Functions

In addition to our analysis of the frequency and magnitude of price changes, a key indicator of micro-pricing behaviour is the conditional probability of price changes, given the time elapsed since the previous price change. In common with other work, hazard functions were used to measure these conditional probabilities: the hazard function is calculated as the share of price changes observed in the current period divided by the share of prices that have not changed in previous periods.⁸ In the results presented below, left-censored observations were filtered out so that we could be certain how many months had elapsed since the previous price change.

Based on the CPI microdata, the hazard functions for goods and services prices were notably different. In our data, consumer goods prices are most likely to change in the month after they previously changed (Figure 9), and the probability of a price change falls as more time passes since the price last changed. In contrast, the hazard function for consumer services prices is broadly flat with a notable spike at 12 months, consistent with annual price reviews. Looking through the spikes in the hazard function, the overall profile is arguably more consistent with simple time-dependent pricing models than goods prices alone would suggest.

This heterogeneity was also evident when we drilled down into the broad goods and services categories. Not surprisingly, the hazard function for energy goods exhibited a very large spike in month one, and a steep downward slope thereafter, consistent with the results discussed previously. However, hazard functions for other goods categories also exhibited downward-sloping profiles, with the function for food and non-alcoholic

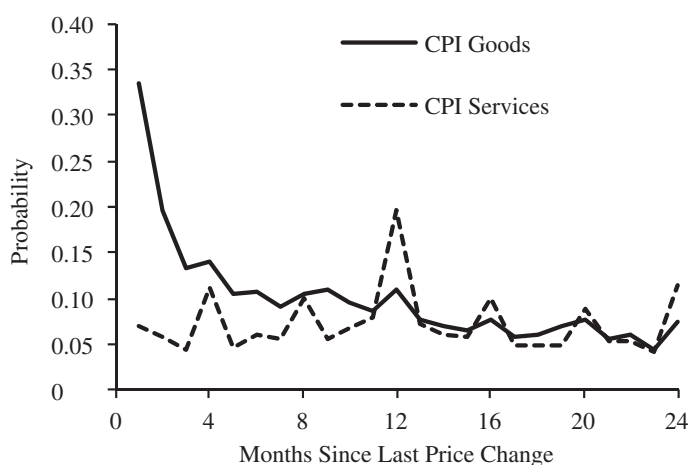


Fig. 9. *Consumer Price Hazard Functions*

Source. CPI microdata.

⁸ For more technical detail on hazard functions, see Bunn and Ellis (2011a).

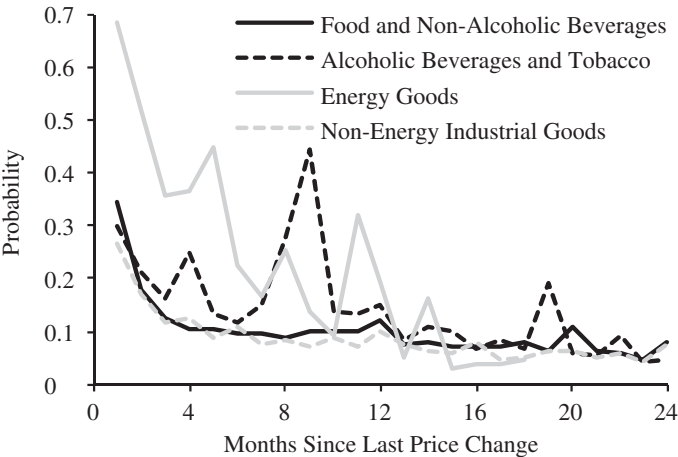


Fig. 10. *Consumer Goods Price Hazard Functions*

Source. CPI microdata.

drinks bearing a remarkable similarity to non-energy industrial goods (Figure 10). The hazard function for alcohol and tobacco is rather more difficult to rationalise, given the notable spike at the 9-month horizon.

There were also similarities between some of the hazard functions for CPI services components (Figure 11). In particular, housing, travel and miscellaneous services all exhibit similar profiles, with spikes at four and eight months and then a larger jump at twelve months, which could be consistent with annual price reviews. The hazard function for recreational and personal services also peaks at twelve months but is much smoother than for most of the other CPI services components. Communication prices appear to behave very differently, but the important caveat here is the fact that our sample is small and significantly underweight relative to the overall CPI basket.

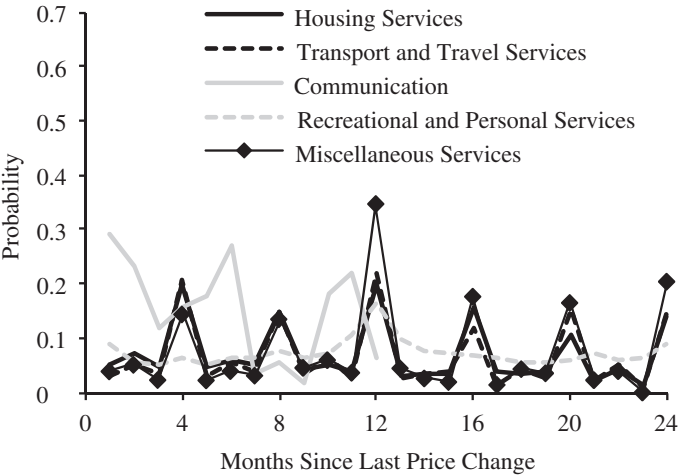


Fig. 11. *Consumer Services Price Hazard Functions*

Source. CPI microdata.

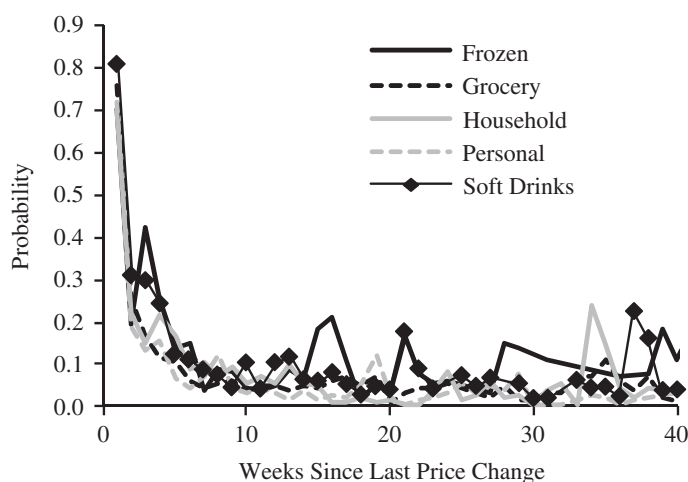


Fig. 12. *Supermarket Price Hazard Functions*

Source. Nielsen microdata.

Hazard functions for the supermarket data exhibited a very similar shape to the hazard function based on CPI goods prices. A selection of hazard functions for different categories is shown in Figure 12. As before, prices are most likely to change in the month following the previous change, and thereafter it is difficult to discern any pattern. All categories shown share this broad shape. The key differences between the supermarket price hazard functions and that for CPI goods data is the difference in the scale of the frequency of price changes, consistent with our previous findings.

The downward-sloping hazard functions that we observe for supermarket and CPI goods prices are inconsistent with a strict form of time-dependent pricing in UK product markets. Such a mechanism – in particular that implied by Calvo (1983) – would imply a flat hazard function. The hazard function for consumer services is much flatter, albeit with notable peaks. Álvarez *et al.* (2005) argue that downward-sloping hazard functions could be a result of aggregation across heterogeneous price setters. They find that, when different groups of price-setters behave differently, it is possible to generate a downward-sloping aggregate hazard function, even if the individual groups follow different Calvo processes. Our disaggregated hazard functions are entirely consistent with this – the hazards functions for prices of different categories of products are very different. Yet, at the same time, we find evidence of downward-sloping hazard functions at the product level, which are not consistent with a single Calvo process for each product. For the result of Álvarez *et al.* (2005) to hold, there must be distinct heterogeneous price setters even at the product level.

4. Implications for Mechanisms of Nominal Rigidity and Policymakers

One of the key motivations for analysing micro-price data is to understand more about how prices behave, and in particular about the degree of nominal rigidity in the economy. These rigidities are key to many macroeconomic and monetary policy

models, particularly regarding the analysis of monetary policy and its impact on real and nominal variables. Neoclassical theory suggests that, with fully flexible prices, monetary policy will have no effect on real output. As such, the degree of nominal rigidity in the economy is therefore a crucial part of the monetary policy transmission mechanism. Different monetary policy models make different assumptions about these rigidities and are typically classified under the time-dependent and state-dependent headings. Each of these pricing models has different implications for the underlying behaviour of consumer prices.

In the data, UK consumer prices do not adjust continually – even using weekly scanner data, not every price changes every month. Even if firms do review their prices continually, the fact that we do not observe continually changing prices is consistent with at least some form of nominal rigidity in product markets.

However, the empirical evidence presented here is not consistent with any one pricing theory that can explain the form of those rigidities. There are pieces of evidence that both support and detract from the different models. For example, the strict Calvo (1983) price-setting model is not consistent with the variation in the share of prices changing that we see in different years and in different calendar months of the year. It is also not consistent with the downward-sloping hazard functions for consumer goods prices, although these could be a result of aggregating across heterogeneous price-setters, as suggested by Álvarez *et al.* (2005).

If state-dependent models with small fixed costs of price adjustment were able to fully explain the nominal rigidities we see in the data, we might expect to see relatively few small price changes in the data. But we find that a significant proportion of all price changes are between -2% and 2% in both datasets, which we regard as small. In light of this observation, for menu costs to play a significant role they would have to be heterogeneous across sectors. But a single, aggregate model incorporating ‘menu costs’ of price adjustment is not consistent with the evidence from UK microdata.

Similarly, a quadratic adjustment cost model, as set out in Rotemberg (1982), also fails to match the data. Rotemberg’s model implies that firms adjust prices continuously, and they move slowly from their previous level to the new optimal level. However, the microdata do exhibit infrequent price adjustment – there is some degree of nominal rigidity – as well as a number of large price changes in the data that are not consistent with gradual adjustment towards an optimal price.

The heterogeneity that we find in pricing behaviour across different industries and product groups is perhaps the most interesting result from our study, and chimes with similar observations from other microdata studies. And this is particularly important for policymakers, as the structural pricing models that are employed at central banks often assume homogeneous pricing agents or uniform underlying pricing behaviour. Certainly most policy-relevant models fall far short of embracing the degree of heterogeneity that we find is evident in the microdata, even when relative prices are included at all (Harrison *et al.*, 2005).

Given this heterogeneity, it is likely that particular theories can better explain pricing behaviour in some sectors than in others, although our results suggest that even at the sectoral level individual pricing theories can struggle. In light of this, it may not be surprising that it is difficult to find any one theory that can explain pricing behaviour at the economy-wide level. Consumer goods prices appear to behave very differently to

services prices. Consumer services prices change far less frequently. One explanation for this is that labour costs will typically make up a greater proportion of the underlying cost of production and delivery in services and labour costs may change less frequently than other costs. The shape of the goods and services hazard functions are also very different; the goods hazard function is downward sloping but the services hazard function is broadly flat with a large annual spike. This heterogeneity argues against the use of 'representative agent' type models.

Aggregation of heterogeneous disaggregated data may overstate the true degree of price stickiness in the economy. This result is also found by Mumtaz *et al.* (2009), who examine the behaviour of disaggregated consumer prices using an empirical model for the UK economy. They also find that persistence in aggregate inflation measures is not matched by underlying price data. This suggests that, if we want to capture the rich heterogeneity of pricing behaviour that we observe in the UK economy and properly understand the impact of monetary policy on those difference prices, we must embrace macroeconomic models that do not rely on unrealistic simplifying assumptions.

5. Conclusions

This article has analysed the behaviour of individual prices using the data that are used in the construction of the UK CPI and using a database of supermarket prices collected from scanner data. There is no previous similar work using UK consumer prices, so our article adds to the micro-pricing literature by being the first to make use of these datasets, and it complements existing work on consumer prices in other countries.

Our study has uncovered several interesting results. First, on average 19% of prices in the CPI basket change each month, although this falls to 15% if sales are excluded. Prices change more frequently in our scanner data from UK supermarkets, and the higher frequency of the weekly data is a key factor here. Second, the probability of a price change is not constant over time; there is variation between the different years in our sample and between different months of the year. The probability of a price change occurring also varies depending on the time elapsed since the previous price change; hazard functions are not flat. Third, the probability of prices changing varies significantly between the different components of CPI. In particular, goods prices change more frequently than service prices. Fourth, the distribution of price changes is wide, although a significant number of changes are relatively small and close to zero.

These results are consistent with the conclusions of micro-pricing studies in several other countries. In particular, the probability of prices changing is not the same in all periods, and the data exhibit significant heterogeneity between the behaviour of prices of different groups of items. The microdata are not consistent with any one theory of price setting, which suggests that different pricing models may be able to better explain price-setting behaviour in different sectors. However, this heterogeneity is ignored in typical 'representative agent' models, while our study of UK microdata, in common with other micro-pricing studies, also finds that prices change more frequently than is implied by the usual micro-founded macroeconomic models. If we want to use micro-founded macro models that match the stylised facts that we observe in the UK

consumer price microdata, the challenge is to develop a new theory of price-setting behaviour that is consistent with these facts whilst also fitting the properties of aggregate data.

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BANK OF ENGLAND

Working Paper No. 378

Do supermarket prices change from week to week?

Colin Ellis

November 2009



BANK OF ENGLAND

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Do supermarket prices change from week to week?

Colin Ellis⁽¹⁾

Abstract

This paper examines the behaviour of supermarket prices in the United Kingdom, using weekly scanner data supplied by Nielsen. A number of stylised facts about pricing behaviour are uncovered. First, prices change very frequently in supermarkets, with 40% of prices changing each week, and even controlling for ‘temporary’ changes, a quarter of prices change each week. Importantly, there is evidence that focusing on monthly observations, rather than weekly ones, overstates the implied stickiness of prices. Second, the probability of price changes is not constant over time — all product categories have declining hazard functions. Third, the range of price changes is very wide, with some very large price cuts and price rises; but despite this, a significant number of price changes are very small. Fourth, there appears to be little link between the frequency and magnitude of price changes — prices that change less frequently do not tend to change by more. Fifth, the strongest correlation between price and volume changes is contemporaneous, suggesting that prices and volumes move together from week to week. And sixth, rough analysis based on simplifying assumptions suggests that consumers are fairly price sensitive: volumes change by more than prices.

Key words: Supermarket prices, behaviour of prices, demand elasticities.

JEL classification: D40, E31.

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The views expressed in this paper are those of the author, and not necessarily those of the Bank of England, the Monetary Policy Committee, the Nielsen Company or Daiwa Securities SMBC Europe Ltd. I am very grateful to Simon Boswell, Alex Bowen, Neal Hatch, Miles Parker, Mike Watkins and especially Philip Bunn and Stephen Hilton, for assistance and useful comments. I hereby claim all mistakes as my own. This paper was finalised on 25 September 2009.

The Bank of England’s working paper series is externally refereed.

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Summary

The object of UK monetary policy is to target inflation, as measured by the consumer prices index, the CPI, at 2% a year. In order for policymakers to keep inflation on target, they need to understand how the actual prices in the economy that underlie official inflation measures behave. One central issue is the degree of nominal rigidity in the economy, the extent to which prices and wages are ‘sticky’. That follows if companies are either unable or unwilling to adjust either quickly, perhaps because of costs of adjustment. This stickiness has profound implications for inflation dynamics and therefore for the conduct of monetary policy.

As a result, a key question for policymakers is how often prices change, and by how much. Early work to investigate this phenomenon often focused on examining the behaviour of aggregate inflation rates at the macroeconomic level. But that can potentially be misleading. So recently economists have spent time examining so-called ‘micro-pricing’ data – the prices of individual products, which may be weighted and aggregated to construct the official price indices.

This paper adds to that exploratory effort, and examines how prices behave for around 280 products in 240 different supermarkets across Great Britain. The data cover a recent three-year period, and were kindly made available to the Bank of England by Nielsen, a market research company. In all, the data set accounts for a little under 5% of annual household expenditure. One big advantage of these data is that they are available at a relatively high frequency – Nielsen collect information on a weekly basis, as oppose to the monthly collection of price quotes often used by national statistical offices. By examining prices and volumes over shorter periods, in particular a week rather than a month, we can shed some light on whether evidence from monthly data may overstate the true degree of price stickiness in the economy – as, by construction, a monthly price series can only change a maximum of twelve times a year.

Several interesting features emerge from analysing the data. Prices change quite frequently in supermarkets – as much as 40% a week, even after trying to strip out temporary promotions and sales – and there is also evidence that monthly price observations can overstate the implied stickiness of prices. The range of different prices changes is very wide, with some very large moves but also many small ones, and there appears to be little link between how much a price changes by and how long it has been since the last time it changed. Prices and volumes – the number of goods sold – tend to move together in the data, and there is tentative evidence that consumers may be quite price sensitive, with volumes changing more than one-for-one when prices change. But, importantly, it must be borne in mind that all of these results relate to supermarket prices, rather than other prices, which may exhibit less flexibility.

1 Introduction

UK monetary policy aims to keep inflation on target at 2% a year. So it is important for policymakers to consider how prices behave. In particular, the degree of nominal rigidity in the economy will influence the short-term impact of nominal interest rates on real activity and the response to inflation to monetary policy.

The notion of nominal rigidity is a feature of many economic models. Essentially, these models assume that companies are unable to freely adjust their prices. A variety of mechanisms have been put forward to explain this assumption. These include costs of adjusting prices (Rotemberg (1982) and Mankiw (1985)), staggered price contracts (Taylor (1980)), threshold or so-called ‘s,s’ pricing (Sheshinski and Weiss (1977)), and fixed probabilities of being able to change prices (Calvo (1983)).

One popular pricing model that results from the last approach is the so-called New Keynesian Philips Curve (NKPC). This relates current inflation to future expected inflation and the deviation of marginal cost from its steady-state value. One feature of these models is that, when estimated, they imply price durations – how long, on average, it takes for companies to change their prices.¹ Early estimates of the NKPC implied that firms changed their prices every 15 to 18 months (Gali and Gertler (1999)), although some estimates have suggested that prices change once every two years (Smets and Wouters (2003)).²

These timings are somewhat longer than evidence from direct surveys of companies’ price setting behaviour – Blinder *et al* (1998) and Druant *et al* (2005) both find that the median price changes once a year in the United States and the euro area, respectively. Other evidence suggests that individual prices may be more flexible than this. In particular, Amirault *et al* (2005) and Bils and Klenow (2004) found that prices change on average every three to four months. And evidence from 300 of the Bank of England’s Agency contacts suggests that half of companies change prices at least five times a year (Bank of England (2006)). One important point of note when comparing results from these various different studies is that sectoral coverage can vary significantly, which may have an impact on the resulting estimates of price flexibility. And the role and treatment of sales, or temporary promotions, appears to be important in measuring price duration – excluding sales and promotions, Nakamura and Steinsson (2008) find the median duration of retail prices is between eight and eleven months.

Kehoe and Midrigan (2007) also examine the role of temporary promotions. Excluding their definition of sales, they find that the implied duration of prices is around four to five months, compared to just three weeks if those sales are included. Somewhat uniquely, Kehoe and Midrigan use weekly store-level scanner data to investigate price frequencies, rather than the more common approach of examining monthly micro-price data, for example in Bunn and Ellis (2009) or Baudry *et al* (2007). As Kehoe and Midrigan point out, while scanner-level data may

¹ McAdam and Willman (2007) find that the Calvo probability parameter defines the upper limit of price duration rather than the average, when NKPC is adapted to include a state-dependent price-resetting signal.

² These papers essentially estimate macro models from which micro-pricing behaviour is inferred. Boivin *et al* (2007) and Mumtaz *et al* (2009) adopt a different approach, modelling aggregate and disaggregated pricing data simultaneously.

be less comprehensive than official micro-price estimates compiled by national statistical offices, its big advantage is the higher frequency of observations. Monthly data give no indication whatsoever about what happens to prices within each month, regardless of whether they are recorded as a monthly average or a point estimate.

This paper follows a similar approach to Kehoe and Midrigan (hereafter KM), and examines weekly store-level data for a sample of UK supermarket products. One difference between this analysis and that of KM and Chevalier *et al* (2000) is that, whereas their data samples are concentrated around one urban sample (Chicago) and are for one retail chain, our data covers the whole of Great Britain and several different retail chains. One key point of note is that, by construction, this paper (and indeed KM) is focusing on prices in outlets where prices may tend to change more frequently than across the wider economy as a whole. Despite recent advances into less traditional product markets, supermarkets still sell more food than anything else – so food will account for a larger share of sales in these data than in, for example, the UK CPI. That must be borne in mind when comparing these results (and KM's) to other work that uses broader but less frequent price data. Indeed, Greenslade and Parker (2008) suggest this may well be the case in the United Kingdom, finding that retailers change their prices much more frequently than firms in other sectors of the economy.

Like KM and Chevalier *et al*, this analysis finds that 'raw' supermarket prices change very frequently, but that some of those changes can be accounted for by temporary discounts. However, even after adjusting for sales prices change very frequently, at least once a month on average. The overall picture is of a considerable degree of price flexibility in the supermarket sector. The next section describes the data used in this analysis, and the following two sections describe results. Finally, the paper concludes.

2 Data

Nielsen is a market research company that provides clients with analysis of sales trends and promotional impacts. To provide this service they collect data from a nationwide network of Electronic Point of Sale (EPoS) checkout scanners which represent sales at 65,000 supermarket and convenience stores in Great Britain. Nielsen maintains a detailed database of different products, covering selling prices, volumes sold, and promotional activities.

This paper uses a bespoke data set created from the Nielsen database. It covers around 240 different supermarkets located throughout Great Britain, covering the largest retailers.³ In total, just over 280 distinct products are included in the data set; however, not all stores stock all products, and some products appear intermittently. The individual products were chosen, with advice from Nielsen staff, both with consideration to brand importance (see Nielsen (2007)), data availability, and to try to get a broad range of different types of goods.

The data set covers selling price and the quantities sold over a three-year period: the data start in the week of 19 February 2005 and end in the week of 9 February 2008. It is worth bearing in

³ Specifically, Tesco, Asda, Sainsbury's, Morrison's, Somerfield and Waitrose.

mind that any results from this analysis are conditional on this sample – in particular in terms of the shocks that hit the UK economy and how they played out over this period. In all, there are just under 5½ million individual price observations, or roughly 35,000 different price observations each week. The price observations are ‘average’ prices for each week: this means that temporary changes in prices, such as selling damaged goods more cheaply, will appear in the data. To the extent that these represent genuine price changes, these observations are useful – they are direct evidence on how easy it is for firms to change prices. But to the extent that these changes represent changes in quality, it may be more preferable to exclude these if we want to focus on underlying prices, for example for identical products.⁴ I took a deliberate decision not to censor or restrict data any further, partly on the basis of these considerations – the aim was to get the ‘cleanest’ version of the raw data without truncating any of the price distribution. Even so, the duration of price trajectories – how long an item is in the data set – varies from product to product and store to store, reflecting both the availability and seasonal demand for various items. But across the data set as a whole, on average over 90% of the sample (by sales values) is observed each week.

Nielsen break the products down into ten different categories: Alcohol; Bakery; Confectionary; Dairy; Fresh (eg fruit and vegetables); Frozen; Grocery; Household; Personal (eg health care); and Soft Drinks. In all, the data set accounts for a little under 5% of annual household expenditure.

Sales values for each category, as a proportion of total sales in the data set, are shown in Table 1: the Fresh category clearly dominates. In the results that follow, this high weight must be borne in mind.

Table 1: Share of sales by product category

<i>Category</i>	Frequency		Sales	
	<i>Number</i>	<i>Percentage of total</i>	<i>£ million</i>	<i>Percentage of total</i>
Alcohol	319,195	5.6	6,449	5.9
Bakery	161,087	2.8	1,624	1.5
Confectionary	544,268	9.6	2,318	2.0
Dairy	614,746	10.8	12,778	11.7
Fresh	1,030,831	18.1	61,890	56.7
Frozen	255,294	4.5	1,986	1.8
Grocery	1,234,536	21.7	10,323	9.5
Household	408,352	7.2	3,430	3.1
Personal	492,449	8.7	2,460	2.3
Soft Drinks	621,778	10.9	6,033	5.5
<i>Total</i>	5,682,536	100	109,110	100

⁴ Averaging could have other implications: for example, multi-buys will reduce average selling prices (which are excluded from ONS data), and a price cut may appear in two separate observations if it happens mid-week. Averaging could also exaggerate the role of temporary promotions, depending on how exactly they are implemented.

2.1 Accounting for temporary changes in prices

As previous work has noted, temporary sales are likely to play a role in any analysis of price changes. While these can be a genuine indication of price flexibility – if firms can change their prices easily and swiftly, that suggests costs of changing prices are low – it is also possible that ‘noise’ in the data may reflect measurement issues (eg multi-buys or quality changes). In addition, if we are interested in focusing on underlying price changes – those longer-frequency changes that may be more likely to reflect macroeconomic conditions – there is a case for smoothing through some of the volatility that temporary price changes will cause. In this paper, headline results from the data – those including all price changes – will be presented alongside results that adjust for temporary changes in prices.

Those temporary changes will be accounted for using three different methods. One method is to examine the so-called ‘reference price’ put forward by Eichenbaum *et al* (2008). This notional ‘reference price’ is simply the modal price within a given quarter. If temporary discounts are important, using reference prices will clearly wash a significant degree of variability out of the raw price data – in particular, reference prices will not change at all within the three-month window.⁵ If anything, this could serve to understate the degree of price flexibility in the economy.

However, the notion of a reference price is a very powerful tool for examining an important question in this paper. One of the key reasons for examining scanner data from supermarkets is that it is available on a significantly higher frequency than other micro data sources. The official micro-price data underpinning the producer prices index (PPI) or CPI will only have one set of observations for each reporting period – each price is only recorded once a month. By construction, this will miss any intra-month variation in prices that may, at the same time, be picked up in our weekly scanner data. Comparing these scanner data with both CPI and PPI micro data is not straightforward, as the former is based on single price observations on a given day of the month, while the latter is based on the notion of an average monthly price. Given that the underlying scanner data are essentially average weekly prices, that suggests they sit somewhere in between the two, although distinguishing precisely where would require a number of (untestable) assumptions.

But what the scanner data can provide is an indication of how much is lost by moving from weekly observations to a single monthly estimate for prices. By constructing monthly reference prices based on the supermarket returns, we can examine what happens to the implied frequency of price duration, compared to the weekly results. The null hypothesis is clearly that it should increase – by construction, monthly data can change less frequently than weekly data. But how much? Scanner data reference prices will shed light on how much we may miss by focusing on the official monthly price data.

In addition to constructing reference prices, this paper will use two other metrics to wash out some of the short-term variation in the data, which could reflect temporary sales. The first is KM’s notion of a ‘regular price’. This classifies price reductions as short-term sales or discount

⁵ The choice of a three-month window seems arbitrary.

offers if they are reversed sufficiently quickly, within some defined period.⁶ For this paper, regular prices are calculated using a window of five weeks, following KM's analysis. So if a price cut is reversed within five weeks, it is excluded from the data. The resulting 'regular price' series is thereby generated from the observed price series, smoothing through these short-term price changes.

One point of note is that this definition of 'regular price' has a similar defining characteristic as a 'reference price' – namely the window of observation and calculation. Both concepts are 'time dependent' in the sense that they are determined by a (subjective) length of time which is used to calculate the adjusted price series. In real life, the pattern of discounts could be heterogeneous between and within product categories, which could make this blanket 'common-window' approach inappropriate.

In light of this, the final method for treating temporary price deviations is free from this consideration of 'window length'. In this paper, I define a 'price reversal' as occurring when prices move either up or down, before exactly reversing at some later (unbounded) point in time.⁷ These price reversals can then be excluded from the data, so that only the remaining observations are treated as price changes.

The unbounded nature of this 'price reversal' concept could potentially lead to long periods of price reversal; but if KM's finding of an average sales duration of two weeks holds in the Nielsen data, then the frequency of price changes should be similar either using 'regular prices' or excluding 'price reversals'. However, the notion of a 'price reversal' also overlaps with the concept of a 'reference price': if most deviations from some 'normal' prices are temporary discounts that are reversed, adjusting for these reversals should yield a clear picture of what that 'normal' price is. If excluding price reversals does drive the frequency of price change sufficiently higher, that could provide some justification for using quarterly reference prices.

3 Analytical results

This section describes the analytical results from examining prices in the data set. Unless otherwise stated, the results presented are weighted by sales values for individual items. The results are grouped into five broad categories, covering: frequency; hazard functions; magnitude; frequency and magnitude; and links between prices and volumes.

3.1 *Headline price change frequencies*

On an unweighted basis, roughly 40% of prices change each week in the data set. On a weighted basis, this is pushed up to 60% (Table 2). One implication of this result is that those items that consumers spend more on tend to change price more frequently. One category, 'Fresh', exhibits more price changes than other categories by some margin, and accounts for a significant part of the higher weighted frequency of price changes. Excluding 'Fresh' products, the weighted frequency of price changes is 40% a week.

⁶ The algorithm is described in detail in the annex.

⁷ This is calculated by considering price changes in pence, as percentages will vary for rises/falls of the same absolute magnitude.

Table 2: Frequency of price changes

<i>Prices changing each week</i>	<i>Per cent</i>
Unweighted	40.9
Weighted	60.0
- <i>excl. Fresh</i>	40.4

There is some variation in the frequency of price changes across categories, with a maximum of 75% a week for Fresh and a minimum frequency of 29% a week for Dairy (Table 3). The frequency of price changes in the data set is split roughly half and half between rises and falls, with no evidence of downward nominal rigidity.

Table 3: Frequency of price changes by product category

Fraction of prices changing each week

<i>Category</i>	<i>Per cent changing</i>	<i>Per cent rising</i>	<i>Per cent falling</i>
Alcohol	58.0	29.0	29.0
Bakery	48.5	24.8	23.7
Confectionary	32.2	16.5	15.7
Dairy	28.6	15.7	12.9
Fresh	75.0	37.4	37.6
Frozen	32.4	16.2	16.1
Grocery	38.8	20.0	18.8
Household	35.7	17.8	17.9
Personal	40.9	20.5	20.4
Soft Drinks	55.1	27.9	27.2

This degree of price flexibility is significantly higher than found in many studies of monthly data, suggesting that examining prices at even a relatively high (monthly) frequency can yield a misleading picture: there is significant variation in prices within the month that monthly data simply do not capture.

However, a significant proportion of these price changes may be attributed to temporary discounts, under either the ‘regular price’ or ‘price reversal’ methods. Focusing on the regular prices method reduces the frequency of price changes to 37% a week, whereas the price reversals method reduces the frequency to 45%. If we then exclude ‘Fresh’ products as well, we find that around a quarter of prices change each week in the data set using both methods (Table 4). The consistency of results from these two different approaches is encouraging and suggests that they may well manage to account for temporary discounts: if the results had been very different, that would have raised concerns that we were not adjusting the data appropriately.

Table 4: Frequency of price changes, adjusting for temporary changes

<i>Prices changing each week</i>	<i>Per cent</i>
Total	60.0
- <i>excl. price reversals</i>	45.3
- <i>based on 'regular' prices</i>	37.3
Excluding Fresh products	40.4
- <i>excl. price reversals</i>	27.0
- <i>based on 'regular' prices</i>	24.3

The majority of price reversals are decreases (followed by increases), which is consistent with most temporary price changes being short-term promotions or sales. One important result from the data is the finding that, on average, the duration of a temporary discount or sale – as defined either using regular prices or by excluding price reversals – is between two and three weeks. That is very close to KM’s findings, and, together with the fact that temporary price changes appear to account for between a quarter and two fifths of all price changes, provides a good guide to the impact of temporary discounts in the data set.

These results suggest that, as in other studies, sales can account for a significant proportion of relatively high-frequency price changes. But unlike other studies, such as KM and Nakamura and Steinsson (2008), excluding sales does not have as large an impact on the implied duration of price changes. Excluding price reversals, 45% of prices still change each week in the data sample (27% excluding Fresh), an implied price duration of a little over two weeks (just under four weeks, excluding Fresh). Looking at regular prices, 24% of these change each week when Fresh is excluded, implying a similar duration of around a month. This is markedly shorter than other estimates in the literature. As mentioned earlier, that is partly likely to reflect the fact our data come from supermarkets, rather than other types of retail output.

3.2 *How misleading are longer-frequency estimates?*

One key benefit of the Nielsen data, as discussed earlier, is its weekly frequency. Many other pricing studies rely on monthly frequency data at best – which, by construction, will limit the implied frequency of price changes. The Nielsen data can offer some insights here – in particular, how big any distortion may be from focusing on monthly data. This can be examined by using Eichenbaum *et al*’s (2008) notion of reference prices – the modal price within a defined period. Two different reference windows were used: a quarterly one, and a monthly one.

In constructing reference prices, one interesting observation was that several items in the data set exhibited multiple modes within three-month periods. In dealing with these, the reference price picked was the highest (maximum) mode within each quarter or month, on the basis that most temporary promotions and discounts were likely to result in lower prices. Table 5 presents results from the reference price series: even excluding the ‘Fresh’ category, 50% of reference prices change each quarter, implying an average duration of six months.

Table 5: Reference prices

<i>Reference prices changing each period</i>	<i>Per cent</i>
Quarterly reference prices	
Total	68.7
Excluding Fresh	50.3
Monthly reference prices	
Total	64.0
Excluding Fresh	44.0

For comparison, 64% of monthly reference prices changed each month, or 44% excluding Fresh products. That implies an average price duration of just over two months, compared with the duration of around half a month implied by the weekly data (again excluding Fresh products). So by moving from a weekly to a monthly frequency – but using the same underlying data – the implied frequency of price adjustment has quadrupled. Indeed, the implied duration from monthly reference prices is twice that found using the regular price of price reversal adjustments, even excluding Fresh products. This strongly suggests that existing duration estimates that are based on monthly frequency data run the risk of overstating the degree of nominal rigidity in the economy. However, our monthly reference prices are still more flexible than new evidence from UK CPI data, which suggest that goods prices change around once every four months (see Bunn and Ellis (2009)). That discrepancy is likely to reflect the source and nature of our data (supermarkets with frequent price changes).

These results clearly demonstrate how the frequency of the underlying data matters – by using long-frequency data, the implied price duration can be considerably higher, and by focusing on such data, be it monthly or quarterly, we may miss much of the higher-frequency variation that is actually present in prices.

3.3 Seasonal factors and price durations

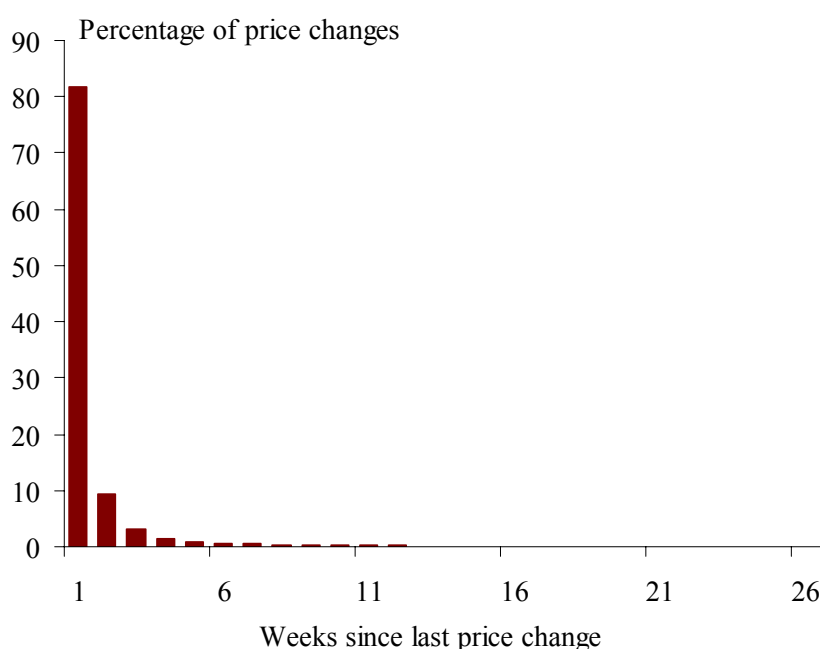
Given these concerns about the impact of looking at monthly averages, the weekly data are likely to offer the best guide to seasonal patterns and price duration. Indeed, the frequency of weekly price changes is broadly constant by calendar month (Table 6), suggesting that seasonal factors do not play a significant role. This is in contrast to Nakamura and Steinsson (2008), who found the frequency of price changes to be highly seasonal in the United States.⁸

⁸ The seasonality of the size (as opposed to the frequency) of price changes is discussed later.

Table 6: Frequency of price changes by calendar month*Fraction of prices changing each week*

<i>Category</i>	<i>Per cent changing</i>	<i>Per cent rising</i>	<i>Per cent falling</i>
January	61.5	29.9	31.6
February	58.5	29.4	29.1
March	59.1	31.6	27.5
April	58.1	28.5	29.5
May	60.0	32.4	27.7
June	61.5	29.1	32.4
July	60.6	28.5	32.1
August	59.4	29.4	30.0
September	58.5	29.2	29.2
October	60.8	30.9	29.9
November	61.6	32.2	29.4
December	60.8	31.4	29.4

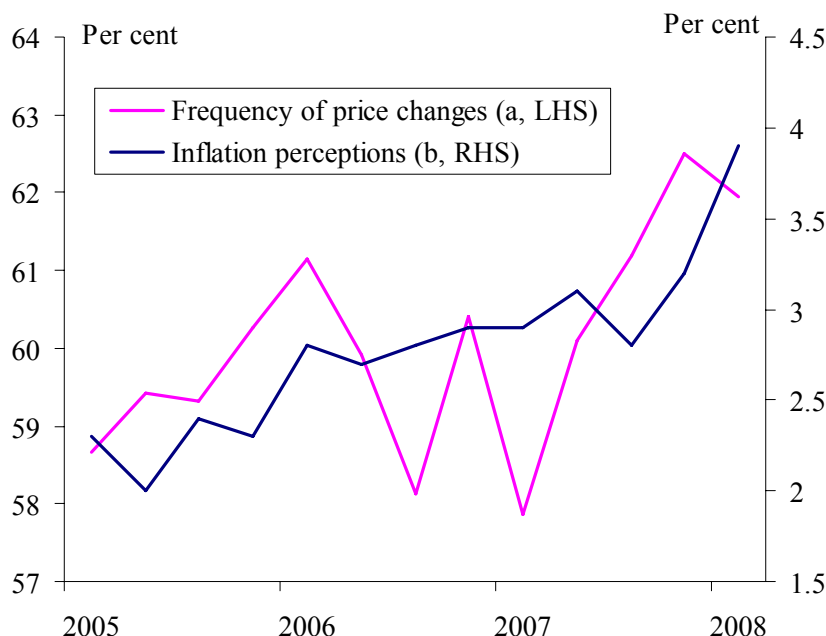
How long do prices tend to persist at a given level? It turns out that the distribution of price durations is highly skewed (Chart 1). In the data set, roughly 80% of prices have changed in the previous week, but the smaller tail of the distribution is very long. Although the average duration of prices is 1.6 weeks (including Fresh), the median duration is just 1 week.

Chart 1: Distribution of price duration

The frequency of price changes also varies somewhat over time within the data sample: this is not surprising, as any change in headline inflation must be accounted for either by more frequent or larger changes in prices (or a shift in the weights towards items with higher inflation rates). Of course, the scanner data do not cover the full range of prices in the CPI or RPI – and while there is evidence of some (lagging) relationship between the two, the strongest correlation

between the difference in price change frequency from quarter to quarter is with the general public's perceptions of inflation, as gauged by the median response in the Bank/GfK NOP survey (Chart 2).⁹ This could suggest that the public's inflation perceptions are influenced by those prices that they observe most frequently (see Driver and Windram (2007)).

Chart 2: Average frequencies and inflation perceptions



(a) Average percentage of prices changing each week.
(b) Survey median.

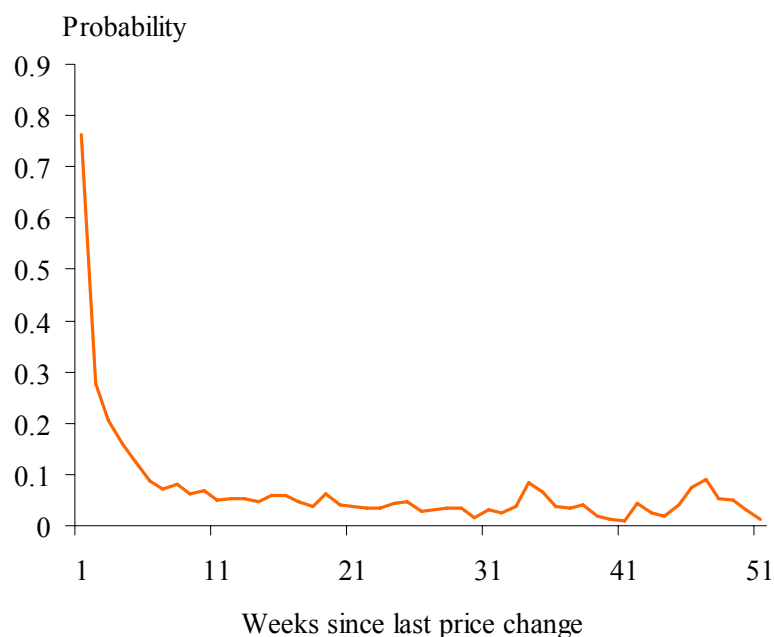
However, it is important to remember that looking at all of the price changes in this manner will double-count items that have multiple changes in the data set. In order to address this, more formal hazard analysis is considered in the next section.

3.4 Hazard functions

Based on the high-frequency Nielsen data, supermarket prices appear to be very flexible indeed. But in part this could reflect products with frequently changing prices appearing many times. In order to investigate this, more formal hazard functions were calculated using the price data. Hazard functions estimate the probability of a price changing at some point in time, given when the previous change in price occurred.

⁹ For more information on the Bank/GfK NOP survey, see Benford and Driver (2008).

Chart 3: Hazard function for all data



The resulting hazard function for the entire data set is shown in Chart 3. The function is sharply downward sloping, as KM found in their analysis. This argues very strongly against any uniform time-dependency framework for price-setting: under these frameworks, the frequency of price adjustment is invariant with regard to price duration, and this is not evident either in these data or in several of the other studies previously mentioned.¹⁰

One concern here may be that raised by Fougère *et al* (2005), who find that aggregate hazard functions can be misleading, and that estimating functions for disaggregated groups of products can lead to very different inference. In the case of the Nielsen data, in actual fact hazard functions for the different product categories are broadly similar (Charts 4a and 4b), with no category exhibiting a constant probability of price adjustment. That could reflect the fact our data come from supermarkets rather than other outlets – Fougère *et al* also find that hazard functions differ across outlet types, noting in particular that supermarkets tend to exhibit decreasing hazard functions. Yet perhaps that is not surprising given that they also estimate that ‘flexible’ prices account for 80% of all supermarket prices. Indeed, these downward-sloping disaggregated hazard functions are consistent with Fougère *et al*’s finding of marked flexibility in supermarket prices.

¹⁰ Alvarez *et al* (2005) get around this problem by positing groups of firms with different frequencies of price adjustment in order to match the data.

Chart 4a: Hazard functions for product categories

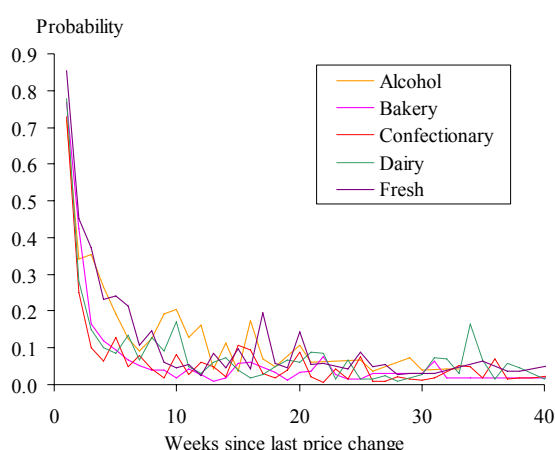
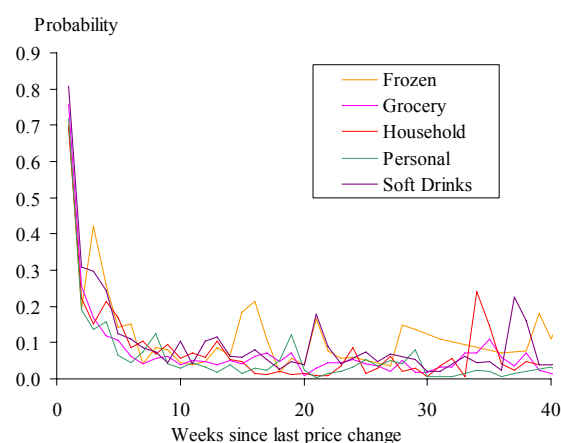


Chart 4b: Hazard functions for product categories



3.5 Magnitude of price changes

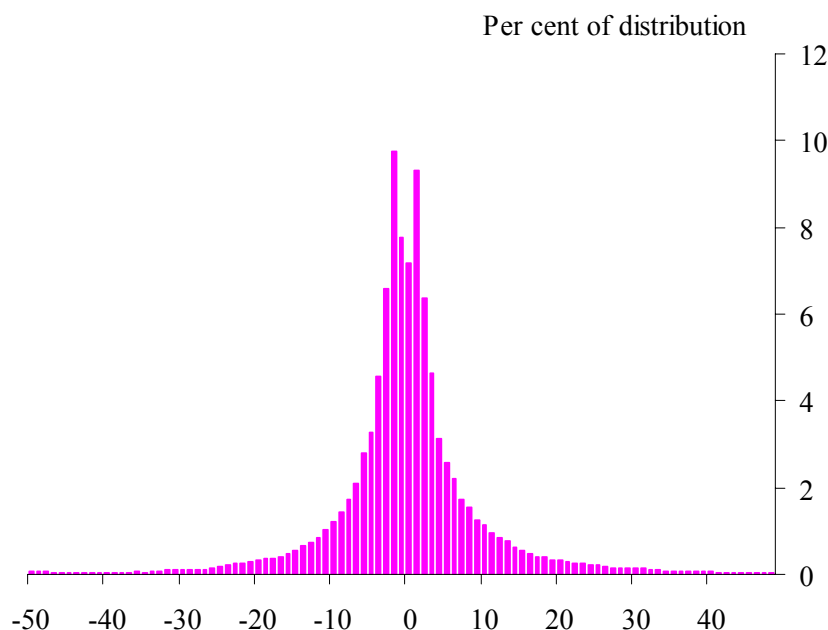
The results so far suggest that prices change quite frequently. But all of the analysis has so far been restricted to analysis of frequency – the results have just observed prices changing without considering how much they have changed *by*. This section examines the magnitude of price changes in the data set.

Across the data set as a whole, the size of changes varied markedly, from around -33% to +45% (Table 7). However, these data represent the tails of the distribution – most price changes were much smaller in size, with the interquartile range being just 6.7 percentage points (pp). Chart 5 plots the distribution of price changes for all observations. The high proportion of small price changes suggests that fixed menu costs are not widespread, while the observed large price changes are contrary to what might be expected if firms faced quadratic costs of adjusting prices.

Table 7: Magnitude of price changes

	<i>Per cent</i>
Mean	0.9
Median	0.2
1st percentile	-32.7
5th percentile	-15.2
10th percentile	-9.1
25th percentile	-3.2
75th percentile	3.5
90th percentile	10.7
95th percentile	18.2
99th percentile	45.2

Chart 5: Distribution of all price changes



Within different product categories there is some degree of variation in the distribution of price changes. Table 8 shows percentiles of the price change distribution for different categories – Soft Drinks appear to have the widest distribution of price changes, followed by Frozen. Alcohol and Bakery have the slimmest distributions.

Table 8: Percentiles of price change distribution by category

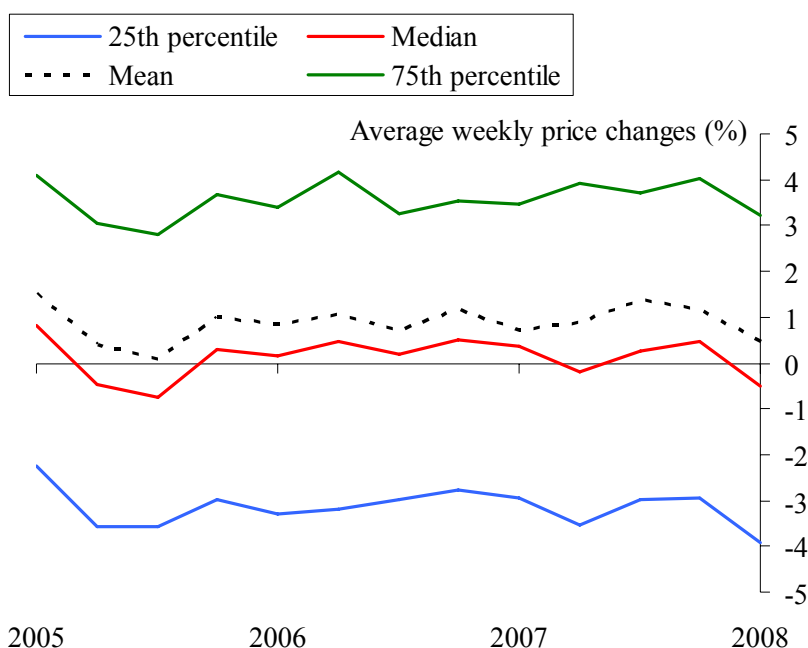
Percentage change in prices

Category	Mean	Median	Percentiles			
			5th	25th	75th	95th
Alcohol	0.5	0.0	-12.5	-1.6	2.0	14.1
Bakery	0.8	0.9	-12.2	-2.2	3.2	14.5
Confectionary	1.2	0.5	-19.0	-3.3	4.3	21.1
Dairy	1.3	0.7	-13.0	-1.6	2.8	16.3
Fresh	0.7	-0.2	-14.1	-3.4	3.6	16.7
Frozen	1.9	0.4	-29.0	-2.8	5.5	33.3
Grocery	1.2	0.4	-20.0	-2.3	3.4	22.2
Household	1.6	-0.2	-18.9	-1.3	2.2	19.0
Personal	1.3	0.1	-18.7	-3.4	3.9	21.4
Soft Drinks	2.0	0.4	-29.7	-3.6	4.7	36.8

Interestingly, the distribution of price changes varies relatively little by calendar month – as with the frequency results, this suggests relatively little role for seasonal effects (Table 9). These results suggest that supermarkets are not the typical venues for large seasonal sales, which may be more apparent in other CPI categories such as furniture. One observation is that the average price change increases over the sample, but the median is more stable (Chart 6). This suggests that the distribution of price changes became more skewed over time in the Nielsen data.

Table 9: Percentiles of price change distribution by calendar month*Percentage change in prices*

Month			Percentiles			
	Mean	Median	5th	25th	75th	95th
January	0.3	-0.4	-18.6	-3.9	3.5	18.4
February	0.8	0.2	-12.7	-2.9	3.1	15.8
March	1.3	0.6	-13.6	-2.7	3.8	17.2
April	0.6	-0.3	-16.0	-3.5	3.3	18.9
May	1.9	0.7	-13.9	-2.8	4.9	22.3
June	0.0	-0.5	-21.6	-4.1	3.3	17.7
July	0.7	-0.5	-16.0	-3.4	3.3	18.9
August	0.8	-0.2	-13.3	-2.9	3.3	16.7
September	0.7	0.1	-13.2	-3.0	3.2	15.5
October	1.1	0.3	-13.8	-2.9	3.8	18.4
November	1.3	0.5	-13.0	-2.8	3.9	19.0
December	1.0	0.4	-16.3	-2.9	3.6	17.6

Chart 6: Summary measures of price changes

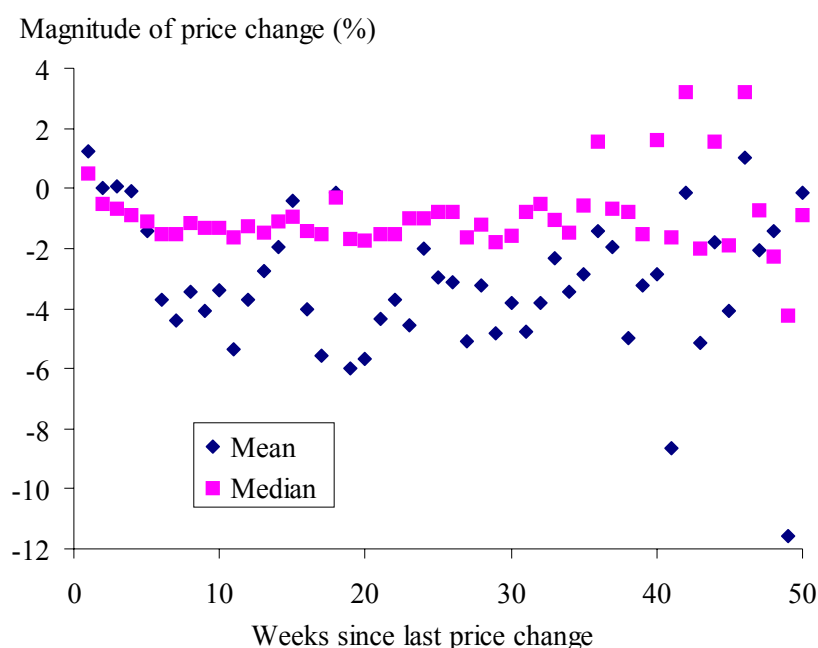
3.6 Frequency and magnitude of price changes

Having examined the frequency and magnitude of price changes separately, this section considers linkages between the two. If prices are set intermittently, larger price changes may occur when the duration of the previous price is large.

Chart 7 is a scatter plot of average and median price changes against the duration of the previous price that was set. One important point to note is that there are relatively few observations beyond three weeks duration, as most prices change more frequently than that. There is little sign that longer-lasting prices are (eventually) changed by greater amounts than prices with

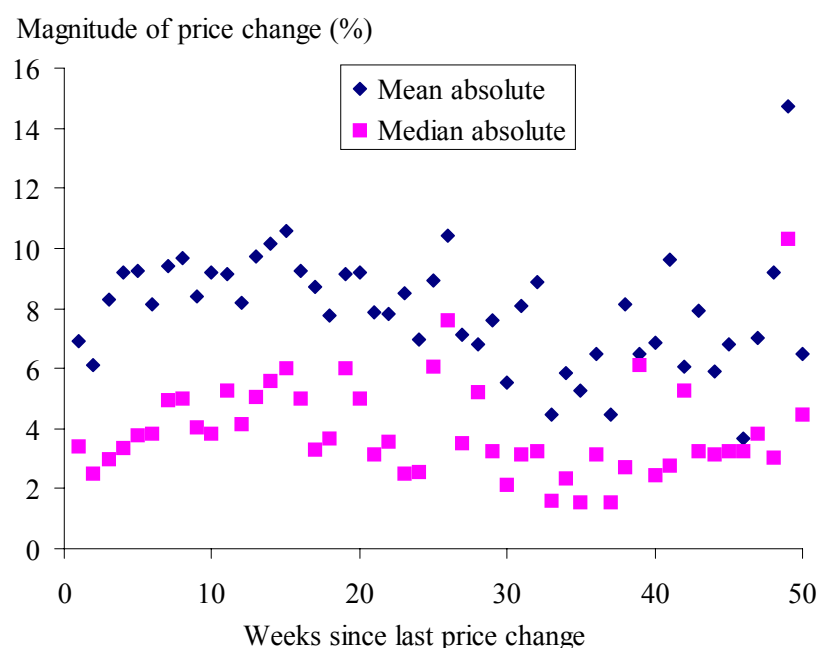
shorter durations. Indeed, econometric investigation confirmed that there were no significant or stable relationships between the magnitude and frequency data in Chart 7.

Chart 7: Frequency and magnitude of price changes



In part, this could reflect large positive and negative changes offsetting each other. So Chart 8 plots similar series, but this time for the average and median absolute price change. Once again, there is no sign of a stable relationship, either from the chart or econometric analysis based on the same data.

Chart 8: Frequency and absolute magnitude of price changes



4 Comparing movements in volumes and prices

4.1 Changes in volumes

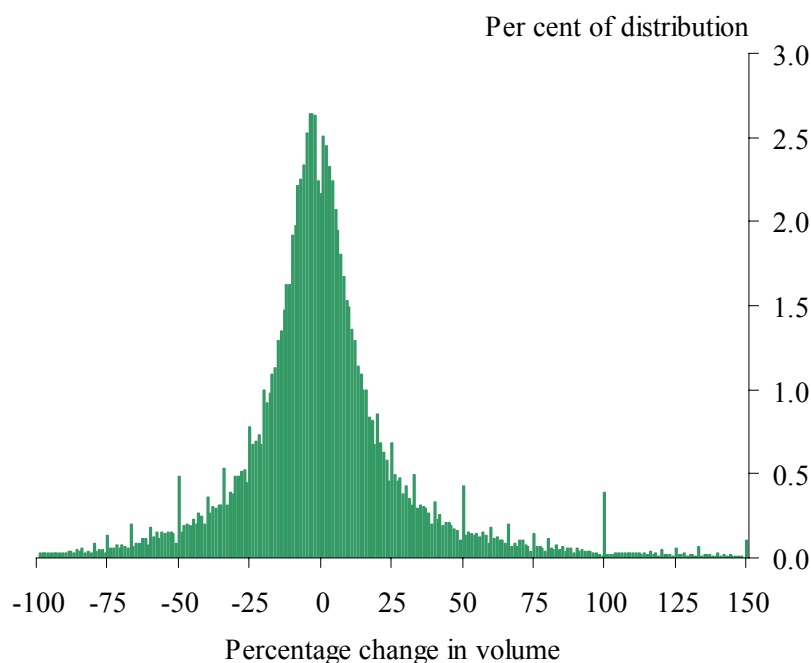
One advantage of the Nielsen data set is that sales data are included alongside prices. This enables some examination of the relationship between changes in price and changes in volume.

Table 10 reports summary statistics on the distribution of volume changes in the data set. It is readily apparent that volume changes are more dispersed than price changes (Table 7): the interquartile range is 24.7pp, compared to 6.7pp for price changes. The skew in the distribution of volume changes also appears to be larger than for prices, reflected in the wider gap between the mean and the median.

Table 10: Percentage changes in volume

	<i>Per cent</i>
Mean	22.4
Median	-0.3
5th percentile	-44.3
10th percentile	-28.6
25th percentile	-11.5
75th percentile	13.2
90th percentile	40.0
95th percentile	74.5

This larger skew is also evident when the whole distribution of volume changes is plotted (Chart 9), particularly in the longer right-hand tail. Large changes in volume are evident in all product categories (Table 11), albeit to a lesser extent for Bakery, Dairy and Fresh, suggesting these categories exhibit less volatile demand, consistent with less substitution between individual products.

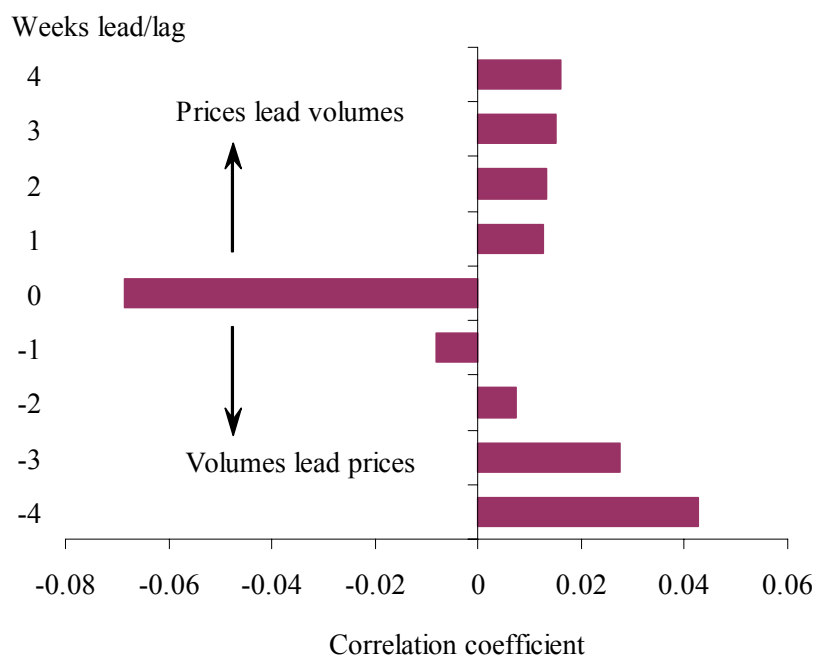
Chart 9: Distribution of volume changes**Table 11: Changes in volume by product category***Percentage change in volumes*

Category	Mean	Median	Percentiles			
			5th	25th	75th	95th
Alcohol	41.20	1.8	-66.7	-27.3	37.8	200.0
Bakery	7.40	1.1	-39.1	-11.6	14.7	60.0
Confectionary	22.70	2.3	-60.0	-21.1	29.0	133.3
Dairy	8.60	0.2	-33.5	-8.7	9.9	46.2
Fresh	9.10	-0.4	-30.9	-9.1	9.9	46.4
Frozen	34.00	-1.2	-58.3	-20.9	25.0	136.8
Grocery	33.90	0.2	-53.4	-17.0	20.0	106.9
Household	225.60	-0.8	-80.0	-27.3	33.3	454.4
Personal	26.30	1.6	-62.5	-27.8	38.5	166.7
Soft Drinks	36.20	-0.7	-60.9	-22.3	27.5	150.7

4.2 Correlations between volumes and prices

The previous section examined the magnitude of volume changes from week to week. One interesting question is whether these changes in volume lead or lag price changes. In practice, prices and volumes are jointly determined by the interaction of supply and demand. But it may be the case that consumers are surprised by changes in prices, and take time to adjust their spending patterns, or that producers take time to change their prices in response to shifts in demand.

Chart 10: Cross-correlations between price and volume changes



Do prices tend to move at the same time as volumes? Simple pair-wise correlations return relatively low estimates, but in fact given the large sample sizes these were often significant (Chart 10). The positive correlation where volume leads price is consistent with stronger (weaker) demand leading to higher (lower) prices; whereas the negative contemporaneous correlation is consistent with customers responding quickly – ie in the same week – and increasing (decreasing) purchases of items with price cuts (rises). However, while these correlations are useful in showing how the data behave, without more detailed information on these changes, we cannot establish whether price or volume changes (or both!) reflect either demand or supply shocks. As such, these results should not be overinterpreted. In the data, prices and volumes move coincidently; but further inference requires more information or more assumptions about the underlying behaviour of firms and consumers.

4.3 Constructing proxies for product elasticities

The strongest correlation between prices and volumes occurs contemporaneously, indicating that prices and volumes tend to move together. But how much do volumes change when prices change, and *vice versa*? Ideally, the way we should answer this question would be to construct formal price elasticities of demand (PEDs).

Technically, in order to examine how demand (volume) responds to price changes, other variables such as income, preferences, expectations and seasonal purchases should be taken into account. All of these factors could result in the demand curve shifting either out or in. In these instances, *ceteris paribus*, we would observe changes in prices and quantities while the elasticity of demand – the slope of the demand curve – may actually be unchanged. In the same manner, we should also control for movements in the supply curve. By accounting for all of these factors, we can attempt to isolate shifts in the demand curve from movements *along* the demand curve – which will provide genuine measures of the elasticity of demand.

Unfortunately, these demand variables are not readily available on a weekly basis. Instead, the assumption I make here is that the high frequency of the data itself acts as a natural control for shifts in the demand curve. The underlying assumption is that, for most households, income and preferences (etc) do not change from week to week. This implies that weekly changes in prices and volumes are more likely to reflect movements along the demand curve – as, by assumption, the determinants of demand to not change as often.

Of course, in the limit this assumption is almost certainly wrong. In any given week, some households will experience large changes in their circumstances – for example, losing their jobs. And in other weeks seasonal effects may drive the consumption patterns of many consumers. Both of these instances – low-frequency changes in households’ circumstances, or temporary seasonal changes in demand – would affect the weekly price and volume data, making it difficult to recover a formal PED.

However, these factors do not affect all households for every week in the data sample – Christmas only happens once a year and only a fraction of workers lose their jobs in any given week. As such, where these large shifts do occur – be they either seasonal fluctuations or large changes in some individuals’ circumstances – the resultant impact on prices and volumes should show up in the tails of the respective distributions for the data sample as a whole. As such, by focusing on the median of the distribution, rather than the mean, the impact of infrequent changes in these potentially large demand factors can be excluded. Essentially, this approach assumes that median weekly (high-frequency) price and volume changes are supply driven, rather than reflecting demand – or, put another way, it assumes that changes in the demand determinants drive large rather than small changes in prices and volumes at the individual store and product level. Clearly this is still an oversimplifying assumption – but it does offer a way of calculating approximate PEDs by exploiting the weekly frequency of the Nielsen data.

The approximate PEDs (*aped*s) are therefore calculated as the medians of the distribution of the ratio of volume changes to price changes:

$$aped_i = \frac{\% \Delta volume_i}{\% \Delta price_i}$$

Table 12 presents summary statistics for the distribution of approximate PEDs by product category. The estimated positive elasticities at the higher end of the distributions – which imply that volumes rise when prices rise – is likely to precisely reflect changes in the determinants of demand other than price, such as income or seasonal effects, that are not controlled for. Indeed, the lack of any formal controls for these non-price factors contributes to the considerable variability in the data, although some of this variability could also reflect genuine instability – ie the response of sales to a given price change may not be constant in the data sample, either over time or by magnitude.

Table 12: Approximate price elasticities of demand by product category

Category	Percentiles				
	5th	25th	50th	75th	95th
Alcohol	-190.7	-22.8	-5.1	5.8	135.2
Bakery	-24.9	-6.0	-1.6	2.2	17.4
Confectionary	-54.2	-10.6	-2.7	2.9	36.3
Dairy	-32.9	-6.4	-1.2	2.5	24.1
Fresh	-16.2	-2.9	-0.5	2.0	14.0
Frozen	-70.8	-11.7	-2.6	1.8	37.5
Grocery	-44.8	-8.2	-2.2	2.6	34.5
Household	-268.5	-23.0	-3.4	7.6	119.5
Personal	-101.3	-13.0	-3.0	4.7	72.9
Soft Drinks	-43.0	-9.3	-2.7	1.2	32.4

As discussed, in order to make any inference about elasticities it is most sensible to focus on the median estimates in Table 12. For most products, these indicate relatively elastic demand, as the magnitudes of the PEDs are greater than one. This indicates that volumes tend to change by proportionately more than prices, consistent with the distribution of volume changes being more dispersed than the distribution of price changes (Charts 5 and 9). The exception is for ‘Fresh’ products – this suggests consumers buy a steadier volume of fruit and vegetables as prices change, compared to other products. However, this may reflect ‘Fresh’ products being defined in terms of large catch-all categories, whereas other product types are more precisely branded, reflecting greater product differentiation. Interestingly, those products that tend to be more storable over time – such as alcohol and household goods – exhibit higher elasticities, consistent with consumers ‘stocking up’ when prices fall. So while these results are clearly approximations at best, and must be treated with caution, there is a sensible economic interpretation of the pattern of estimates that is uncovered.

5 Conclusions

This paper has examined how prices in UK supermarkets behave, using scanner data from Nielsen that are available on a weekly frequency – in all, the data set accounts for a little under 5% of annual household expenditure. This paper therefore adds to the growing literature of micro-pricing studies.

Using these data, several interesting features emerge about how prices behave. First, prices change very frequently in supermarkets – 40% of prices change each week (excluding ‘Fresh’ items). Some of these price changes are likely to be temporary – but even when we control for these by excluding price reversals or smooth through temporary price falls and look at ‘regular’ prices, we still find that roughly a quarter of prices change each week. Importantly, there is also evidence that focusing on monthly observations, rather than weekly ones, overstates the implied stickiness of prices. Overall, the results suggest that prices in supermarkets exhibit a greater degree of flexibility than may be evident in other sectors. Second, the probability of price changes is not constant over time – all product categories have declining hazard functions. Third, the range of price changes is very wide, with some very large price cuts and price rises; but despite this, a significant number of price changes are very small. Fourth, there appears to

be little link between the frequency and magnitude of price changes – prices that change less frequently do not tend to change by more. Fifth, volume changes exhibit at least as much variation as price changes, and the strongest correlation between the two is contemporaneous, suggesting that prices and volumes move together from week to week. And sixth, rough analysis based on simplifying assumptions suggests that consumers are fairly price sensitive.

Overall, these results suggest that price stickiness is not a key factor in the UK supermarket sector: indeed, nominal rigidities appear to be quite limited. Prices and volumes change frequently, potentially by quite a lot, and there is significant heterogeneity in the patterns of both prices and volumes.

6 Annex: The ‘regular price’ algorithm

This annex describes the ‘regular price’ algorithm used to define temporary sales in the main paper. It is based on Kehoe and Midrigan (2007).

In their paper, KM construct the regular price series, P_t^R , from the original price series, P_t , as follows. Whenever the actual price series falls, ie $P_t < P_{t-1}$, check if the actual price rises above its current (new) level over the next five weeks: ie, check if $P_{t+j} \geq P_t$ for $j \leq 5$. If it does, then define J as the first time the actual price rises above its current (new) level, P_t .

To construct the regular price series, replace $P_t, P_{t+1}, \dots, P_{t+J-1}$ with P_{t-1} . If the price never rises above P_t within the next five weeks, leave P_t unchanged. This is repeated at different horizons, to allow for a variety of sales patterns. For example, if the actual price series was:

100, 95, 96, 97, 98, 99

then using the algorithm at $t+1$ would yield

100, 100, 96, 97, 98, 99

but using it up to $t+5$ would yield

100, 100, 100, 100, 100, 99

In this way the algorithm was ‘repeated’ by sequentially examining prices over decreasing window. So in the first instance, the algorithm examined if $P_{t+5} > P_t$, and replaced $P_t, P_{t+1}, \dots, P_{t+4}$ if they were (each) below P_{t+5} and P_{t-1} . In the second instance, the procedure was repeated by examining if $P_{t+4} > P_t$, and replacements ensued on a similar basis. As five-week sales periods were already replaced in the first instance, there is no risk of double-counting as the inequality conditions will not be met in the second instance. The resulting series for the sample data is the same as is shown above, but is also robust to other patterns: eg 100, 90, 85, 102, 98 becomes 100, 100, 100, 102, 98.

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Measuring UK inflation

Practical differences and issues

Colin Ellis

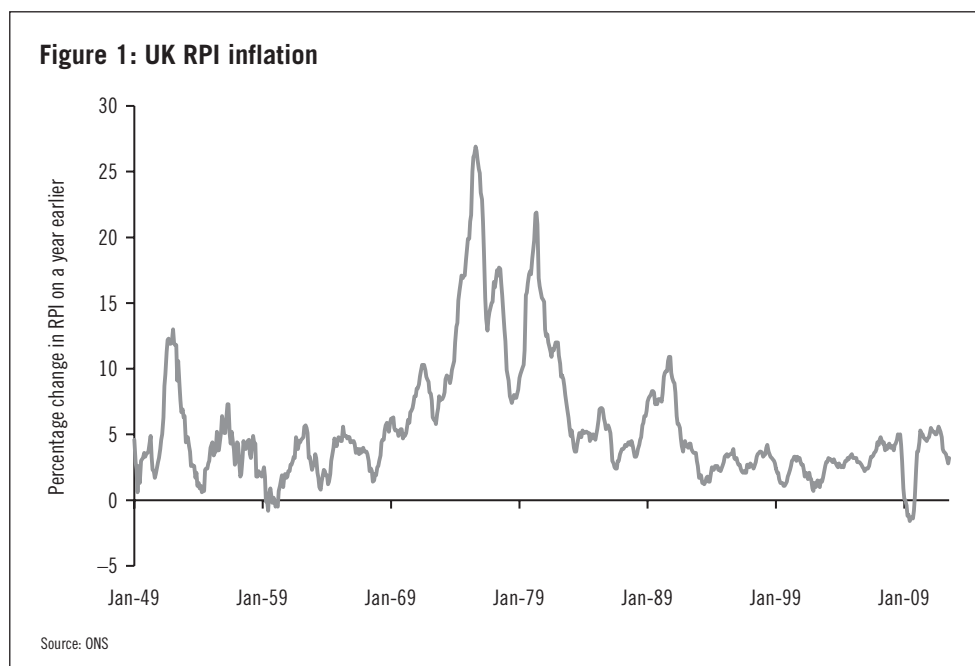
The importance of measuring inflation

Inflation, along with other macroeconomic variables such as GDP growth and unemployment, is one of the key indicators that policymakers seek to influence. After periods of very high inflation during the 1970s, and to a lesser extent in the late 1980s, monetary policy generally focused on the goal of achieving low, stable inflation rates. In the UK, this policy was formally adopted in 1992 following sterling's exit from the European Exchange Rate Mechanism, and was subsequently delegated to the Bank of England when the independent Monetary Policy Committee was established in 1997. While inflation has recently been somewhat higher than in the early years following Bank of England independence, inflation in the UK economy has remained relatively contained, at least compared with the 1970s (Figure 1).

Inflation measures the change in the general price level in a given economy or region. High inflation matters because it swiftly erodes the purchasing power of money – an annual inflation rate of 10% means that a given nominal sum of currency will buy roughly 10% fewer goods and services in a year's time. In that sense, inflation is truly a monetary phenomenon, although changes in individual prices – or relative price shifts



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– can also drive shifts in measured inflation in the short to medium term (see Mumtaz *et al.* 2009). But the process by which inflation is measured is far from simple; and, even within a developed economy such as the UK, different approaches are taken for different measures of prices.

Alternative approaches can result in differences between measured inflation rates, and these matter for monetary policy makers. One of the key judgements that policymakers need to make is whether an

Does an observed move in an inflation measure reflect generalised inflationary pressure or a one-off relative price shift?

observed move in an inflation measure reflects generalised inflationary pressure throughout the economy; or, instead, just a one-off move reflecting a particular relative price shift or component of the price

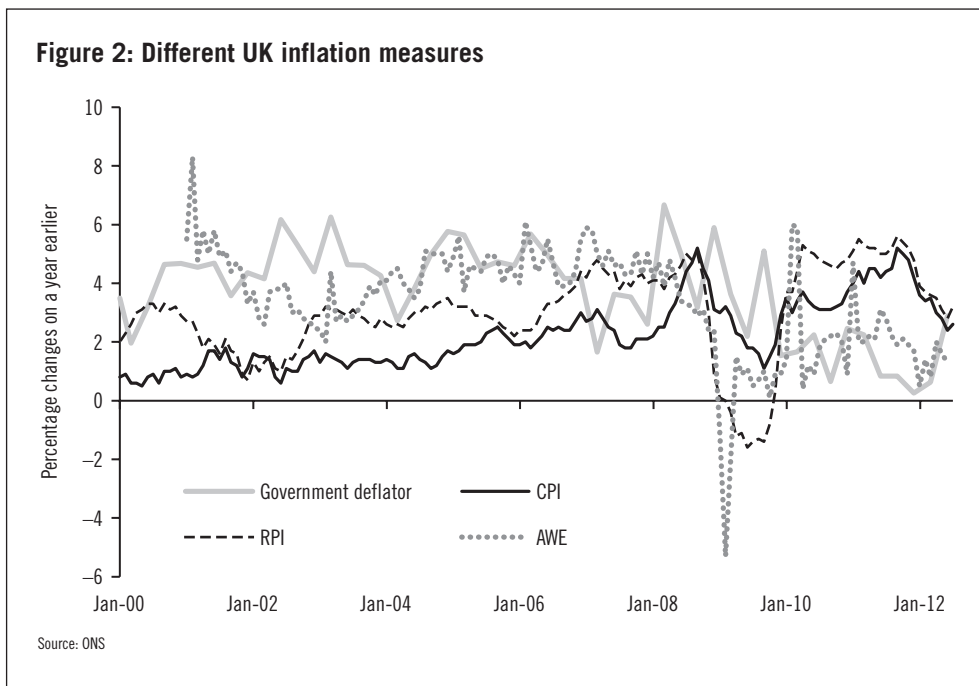
index in question. In principle, generalised inflationary pressure should be evident in many different measures of inflation, including consumer prices, producer prices and wages. But, without understanding how the construction of these measures differs, policymakers may struggle to interpret the different signals they observe from different measures of inflation. Furthermore, it is possible that the very process of calculating an

aggregate inflation measure can also influence its behaviour, relative to the disaggregated prices from which the aggregate measure is ultimately constructed. It is important to understand these issues if we want to interpret signals from measures of inflation.

Underlying data-gathering processes

The starting point for any inflation measure is an underlying index from which to calculate changes in prices. This paper considers some broad inflation measures that are often referenced in the UK, based on: retail and consumer prices; producer prices; average weekly earnings; and a specific component of the GDP deflator, namely the implied government expenditure deflator. These different measures of inflation are shown in Figure 2. By examining the sources and methods behind these different measures of price changes, we can better understand how different inflation measures relate to one another.

The starting point for any price index is the gathering of raw data. However, the method of doing so varies substantially.



In the case of the retail prices index (RPI) and consumer prices index (CPI), the majority of underlying price data are collected locally. To facilitate this, ONS price collectors go to shops around the second or third Tuesday of every month, known as 'Index Day', and record the selling prices that they observe. These locally collected data make up around two-thirds of the overall CPI by weight.¹ The remaining prices are collected centrally by the ONS, and are typically national prices from particular companies (Bunn & Ellis 2012). Around 180,000 separate price quotations are used each month. The main coverage differences between the CPI and RPI relate to owner-occupied housing costs, which are currently excluded from the former (differences in weighting and methodology are discussed later).²

The RPI and CPI employ detailed processes to eliminate potential outliers from the data – unusual or extreme observations that could distort the aggregate picture. Before locally collected prices are transmitted to the ONS, several checks are carried out by collectors. The observed price is compared with the price for the same product, in the same shop, in the previous month (if possible). A 'price change' check then warns collectors if the percentage change exceeds pre-specified limits for different items. The price will also be checked against a 'min/max range' determined on the type of item and derived from the latest (non-zero) price for the same product. After the locally collected data are sent to ONS, these local checks are reapplied. In addition, a process known as the Tukey algorithm is employed to detect and remove outliers.³

The data underlying the producer prices index (PPI) are collected in a different fashion. Instead of directly collecting observed prices, most of the raw data underlying the PPI are based on a monthly ONS survey of UK businesses that are registered for VAT or PAYE.⁴ Roughly 4,000 businesses are sampled from a population of around 140,000 firms, based on the Inter Departmental Business Register (IDBR). The sample is stratified by sales and product classes. In response to the survey, firms return input (cost) and factory gate (output) price quotes to the ONS, with around 6,750 price quotes provided for home sales. Apart from computers,

¹ One notable difference is that CPI prices for petrol and oil are averaged over the month based on prices each Monday. In the RPI, these prices are collected alongside others on Index Day.

² Efforts are currently under way to include these costs in the CPI from February 2013.

³ ONS (2012) provides further detail on this process, in addition to other checks not detailed here.

⁴ Some data are collected by DEFRA and BIS.

where a hedonic model is used to adjust for changes in quality, the survey relies on advice from respondents when the specification of a particular item changes; the goal is that only the ‘pure’ price change is recorded. This means that, unlike CPI/RPI, the PPI is far more reliant on reported (as opposed to observed) micro-level data. In marked contrast to the CPI/RPI, there is no formal routine for detecting/treating outliers. Instead, atypical and extreme returns are typically identified as part of the general validation of survey responses, and businesses are contacted to check accuracy in these instances.

One consequence of both CPI/RPI and PPI data collection is that the highest possible data frequency is monthly. This means that, at most, prices can change 12 times a year – once each month. This is an important constraint when considering underlying economic structures such as the degree of price flexibility. Evidence from higher-frequency data suggests that, in some instances, prices may change more frequently than once a month (Ellis 2009). As such, the collection of monthly data can overstate the implied stickiness of prices.

The average weekly earnings (AWE) measure is more akin to PPI than CPI. The data source for this series is the Monthly Wages and Salaries Survey (MWSS), which collects information from around 8,500 businesses with 20 or more employees. As with other statistical surveys, the sample is stratified by employment bands and industrial classification, and based on the IDBR. Average wages in small firms are estimated based on observed wages in large firms, multiplied by an adjustment factor that is derived from the Annual Survey of Hours and Earnings (ASHE). In light of previous concerns about the impact of only using data from firms that stay within the sample,⁵ missing data are imputed where appropriate. Outliers are detected automatically using statistical techniques, based on extreme wage levels rather than changes in earnings.

A final indicator of interest relates to the GDP deflator. While not formally an inflation index, the GDP deflator is often regarded as an approximate measure of whole-economy inflation. By definition, consumer price or wage indices only focus on one particular sector or market of the economy – coverage is incomplete. The GDP deflator, in contrast, should in principle capture and aggregate all prices in the economy.

⁵ This is the potential bias arising from using ‘matched pairs’, as discussed in Weale (2008).

Formally, the UK GDP deflator is the ratio of the current price estimate of GDP to the (chained) volume measure of GDP. In the reference year, the deflator will be 1, or normally indexed to 100. Current-price GDP data are collected via ONS business surveys, while the volume measure of GDP is typically constructed by deflating these nominal data using price information already collected for the CPI or PPI. But there is one area where a different process is followed: that of government consumption and output.

Unlike other output and expenditure categories, the measurement of public sector activity poses unique issues for statisticians. Overall, public

Measuring public sector activity such as healthcare and education poses unique issues for statisticians.

services such as healthcare and education account for around a fifth of UK GDP. But this government output is not normally categorised as market output, as it is not sold

(or intended for sale) at prices determined by the normal interaction of demand and supply. Instead, the government is typically considered as the procurer (and provider) of these services on behalf of its citizens. In the absence of a market price, it is difficult to deflate current price estimates of output or spending to obtain volume estimates. However, at the same time, the previous long-standing ‘input equals output’ convention for measuring public sector output implied that public sector productivity would always be zero. This posed practical challenges for economists and statisticians alike.

In light of this, in 1998 the ONS started to measure public sector output using direct methods – based on observed volume series such as the number of patients treated, or the number of children passing GCSEs. This work was given renewed impetus by the Atkinson Review of government output and productivity (Atkinson 2005), and by 2008 roughly 60% of government output was measured using direct output methods (Pont 2008).

This means that, for a major component of GDP, its deflator is largely not based on price data at all. As with other expenditure components, the government deflator is the ratio of current price spending to the volume estimate of output; but that output estimate is primarily independent of any observed prices. As such, changes in the government deflator provide a measure of inflation that is largely not based on observed prices at all.

This is in obvious contrast to the other inflation measures described earlier.

To sum up, official measures of consumer prices, producer prices and earnings are all based on different methods of price data collection and cleansing, while the government deflator is largely not based on price data. These differences will contribute to differences between the measured inflation rates. But aggregation and weighting techniques also vary, further complicating matters. These are discussed in the next section.

Aggregation and weighting

Once underlying data have been collected, they then need to be aggregated into a single index representing the general price level. Such indices measure prices against some notional reference point or base period.

Two basic price indices are the Paasche and Laspeyres indices. The Paasche index calculates the sum of current-period prices multiplied by current-period quantities, and divides this by the sum of current-period quantities multiplied by base-period prices. In contrast, the Laspeyres index calculates the sum of current-period prices multiplied by base-period quantities, and divides this by the sum of base-period quantities multiplied by base-period prices. A Laspeyres index will tend to overstate inflation because it does not account for the fact that consumers typically react to price changes by changing the quantities that they buy. A Paasche index, based on related reasoning, tends to understate inflation.⁶

In the UK, the RPI and CPI are constructed as ‘quasi-Laspeyres’ indices.⁷ Both indices are constructed on a ‘bottom up’ basis, with individual prices within detailed categories first aggregated into initial sub-indices. This lowest level of aggregation has about 5,000 indices, subdivided by region and type of shop. As there is no information on expenditure shares at this detailed level, these initial sub-indices are typically calculated as unweighted averages of the collected prices. These sub-indices are then

⁶ The Fisher index, calculated as the geometric mean of the Laspeyres and Paasche indices, is sometimes called the ‘ideal’ price index.

⁷ They are not true Laspeyres indices because the base period for quantities (expenditure weights) does not exactly coincide with the base period for prices.

weighted together using expenditure shares to create higher-level indices, for particular products such as meat or fish. These higher-level indices are then aggregated into broader categories, such as food, and ultimately into the aggregate price index.⁸

The expenditure shares used as weights in the RPI and CPI are updated on an annual basis at the beginning of each year. The two indices use different sources for their weights data. CPI weights are based on latest National Accounts data, updated for subsequent movements in price indices. The CPI aims to reflect the purchasing patterns of all private households, including visitors to the UK. In contrast, RPI aims to exclude spending by the richest 4% of households (measured by income) and pensioners who are heavily dependent on state benefits. Its weights are based on data from the Living Costs and Food Module (LCF), a continuous survey monitoring the spending of around 6,000 households. Apart from the differences in coverage noted earlier, the differences in weighting methodologies can also drive wedges between observed inflation rates. The annual updating of weights also results in individual items dropping into and out of the basket of goods and services that the indices capture, to reflect changing habits in consumer spending. Both indices are constructed using annual chain-linking, whereby individual price indices within each calendar year are 'linked' together to create a single continuous time series. At the same time, the annual updating of weights implies that measured inflation will not capture price changes in the same set of goods and services over a number of years.

The PPI is also calculated as a Laspeyres-type index but, in contrast to the PPI and CPI, the weights used to construct the index are updated only every five years. This means that, over time, changes in economic structure could potentially drive a wedge between PPI and CPI inflation rates, as the weighting structure in the former would not adjust as swiftly as the latter.

In the case of the AWE, a different approach is taken. One of the key concerns about the now-discontinued Average Earnings Index (AEI) was that it was unresponsive to shifts in the composition of employment. In other words, a shift in jobs from a high-paid to a low-paid sector of the economy would have no impact on wage inflation as measured by

⁸ In addition to the headline CPI and RPI measures, variants such as RPIX (RPI excluding mortgage interest payments) and CPIY (CPI excluding indirect taxes) are also constructed.

the AEI (see Turnbull & King 1999). The AWE was the product of subsequent development work to produce a better measure of earnings that would respond to such shifts in employment patterns. Importantly, changes in employment are accounted for in the AWE, such that a shift in employment from high-wage to low-wage firms shows up as a decline in overall average earnings. Unlike the weights in RPI, CPI or PPI, employment weights are updated each month, based on returns from the MWSS (Parkin *et al.* 2009). This means that, during times of unusual structural changes in spending and employment patterns, the AWE could be a more up-to-date guide of inflationary pressure than the CPI or PPI.

The government deflator is different for other reasons. Apart from being a quarterly series based on nominal spending data and (largely) observed output volumes, the calculation of the deflator means that it is more akin to a Paasche-type price index than the quasi-Laspeyres indices used to calculate CPI and RPI. Under the current chain-linked methodology, weights are implicitly updated annually, albeit with some lag, such that estimates of the deflator during 2012 H1 were implicitly based on 2009 weights.

These differences in construction and weighting mean that policymakers will always need to tread carefully when interpreting signals from different inflation measures, and not just because they reference different economic sectors. In fact, even where inflation measures cover the same sector, such as the CPI and RPI, specific methodological differences can also generate different inflation rates.

Consumer price inflation: the formula effect

Apart from the differences in underlying data and weighting methods, different price indices also use different aggregation methods. This is particularly relevant for the calculation of the CPI and RPI.

Apart from the relatively small differences in weights and coverage described previously, CPI and RPI are essentially different measures of the same thing: they are based on (broadly) the same data, and both track the price of a changing basket of consumer goods and services over time. Yet the way in which that raw data is aggregated to construct a price index varies. In particular, RPI combines individual prices in each detailed product group using arithmetic means, either a ratio of average prices (known

as a Dutot index) or an average of price relatives (known as a Carli index).⁹ The CPI combines the same disaggregated data using geometric means for the first stage of aggregation, and the ratio of averages elsewhere. In practice, the geometric means will always give a lower estimate than the average of relative prices (except when all values are equal), meaning that RPI inflation estimates will be higher than CPI estimates where the Carli index is used. In economic terms, the use of geometric averaging is implicitly consistent with some degree of substitution away from brands or products that have become more expensive to consumers. In contrast, the arithmetic mean is consistent with no substitution between products.

The ONS has labelled this difference in aggregation techniques as the ‘formula effect’ (Roe & Fenwick 2004). At the time of the change in the Bank of England’s inflation target from RPIX to CPI, the formula effect had accounted for around 0.5 percentage points (ppts) of the difference between the two inflation measures. Since then, its impact has become much more pronounced (Figure 3). This wedge between two similar

Figure 3: The formula effect*



*Contribution of different formulae to aggregate prices at the most basic level to the difference between published 12-month RPI and CPI inflation rates. Data are spliced across methodology change.

Source: ONS

⁹ A price relative is the ratio of the current price to the price in the base period.

inflation measures, largely based on the same underlying data, obviously presents a problem for an inflation-targeting policymaker.

The impact of aggregation on time series properties

The various data collection, weighting and aggregation issues described above indicate that policymakers need to be careful when interpreting different aggregate inflation series. However, the very construction of aggregate price indices – measures of the ‘general price level’ across parts of the economy – can also affect the observed behaviour of inflation.

One particular issue for monetary policymakers is the persistence of inflation – how closely inflation in one period is related to inflation in the previous period.¹⁰ The more persistence that inflation exhibits, the more likely it will be to deviate from any target or desired level for a prolonged period of time in response to an economic shock. As such, policymakers may need to respond more forcefully to such shocks in order to limit lengthy deviations of inflation, compared with a scenario in which inflation was not very persistent.

Unfortunately, gauging the true persistence of inflation is not trivial. A number of studies have noted that, while inflation persistence is typically visible at the level of the headline index measure, there is often far less (if any) evidence of inflation persistence at the disaggregated price level. Recent research – in particular Mumtaz *et al.* (2009), and Bunn and Ellis (2010) – has demonstrated that this is true in the United Kingdom. The difference between estimates of persistence at the aggregate and disaggregate level is marked: the persistence of aggregate inflation measures is not the same as the average persistence of the underlying component series.

These differences in persistence are likely to reflect aggregation bias. This arises when the very act of combining different data series into a single measure (or index) changes the observed properties of the data. In the context of inflation measures, it can be thought of as the difference between the pattern of inflation that is derived from aggregate indices, such as CPI and RPI, and the pattern that can be derived from aggregating the patterns of the original disaggregated data.

¹⁰ Note that this analysis focuses on inflation rates in non-overlapping periods: by definition, rates of change across overlapping time periods (such as 12-month inflation rates in consecutive months) will be serially correlated by construction, as noted in Barnes and Ellis (2005).

As Imbs *et al.* (2005) demonstrate, measures of persistence that are calculated from aggregate price indices will be biased upwards when there is heterogeneity in persistence among the disaggregated components. As the behaviour of disaggregated prices in the UK exhibits considerable heterogeneity, as summarised by Bunn and Ellis (2009), this means that estimates of persistence that are based on aggregate CPI or PPI inflation measures will overstate the true degree of inflation persistence in the economy. In a similar vein, Imbs, Jondeau and Pelgrin (2007) find that single-price models, of the type frequently used in monetary analysis, overstate the apparent backward-looking behaviour in prices in the face of such underlying price heterogeneity.

If policymakers are unaware of these biases, then interest rates could be set at inappropriate levels. Quite apart from the differences in data collection and aggregation across different inflation measures, policymakers must be aware of how the very construction of aggregate inflation measures can distort the picture that they present of underlying economic behaviour.

Conclusions

Controlling inflation is an important task for monetary policy makers, but this task is complicated by practical issues arising from the measurement of

The task of controlling inflation is complicated by practical issues arising from its measurement.

inflation – in particular the collection and aggregation of microeconomic price data. Collection frequencies and methods will affect what inferences can be gleaned from inflation series; and different meth-

ods of aggregation, weighting and treatment of outliers can also potentially drive discrepancies between different measures of inflation. Given that one critical aspect of monetary policy is the ability to distinguish between generalised inflationary pressures and individual relative price shifts, it is vital to be aware of these differences in approach. In addition, the very process of constructing an aggregate inflation measure can influence the time-series properties of that measure, as there is evidence of aggregation bias in measures of persistence. All told, these practical issues can materially complicate policymakers' analysis of price pressures and trends, and must be carefully borne in mind when interpreting inflation data.

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Why We Should Change the Inflation Target (But Not in the Way You Might Think)

Colin Ellis¹

The UK economy is in recession. On the back of flat output in 2008 Q2, and the larger-than-expected fall of 0.5% in Q3, forecasters are now falling over themselves to downgrade their projections for UK GDP growth in 2009 and 2010.

Whenever events turn sour, recriminations arise. One claim that has already been made is that the Monetary Policy Committee (MPC) of the Bank of England got policy wrong. By worrying too much about the recent spike in commodity prices, the MPC did not pay attention to the unfolding downturn in the UK economy. The shock 150bp cut in November was a clear admission that the Bank had been behind the curve.

At the moment, the first priority for policymakers is clearly to limit the extent and duration of the recession. Lower interest rates, fiscal packages, government guarantees for Bank lending and mortgages – all are designed to grasp the recessionary nettle and pull the economy back on track. But there has already been discussion about what should happen after the recession – what the appropriate role for policy should be. Some people want to take the UK into the euro. Others think monetary policy should pay more attention to asset prices. In this essay, I will set out two changes to the monetary policy framework that should be adopted once the banking crisis and recession have passed.

How high should the target be?

The Government's monetary policy objective, which the Bank of England is tasked with meeting, is defined in the 1998 Bank of England Act as 'price stability'. In practice, this is then specified as a 2% inflation target, as measured by the Consumer Prices Index (CPI). Authorities around the world have similar arrangements – 'price

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stability' objectives but then a non-zero, positive inflation target.

Why is price stability not defined as zero inflation? Two arguments are commonly given here. The first is that measured inflation tends to overstate the average rate at which prices in the economy rise. One reason for this is product switching – in essence, it is very hard to measure all our small changes in consumption, so the measured rate of inflation overstates the 'true' rate of inflation. These upward biases are hard to eliminate, and one reason to have an inflation target that is above zero.

The second argument relates to how monetary policy works. The MPC set the nominal interest rate – the price of money. Because changes in that interest rate take time to affect demand and prices, the real rate of interest – the nominal interest rate minus inflation – will change. It is changes in this real rate of interest that influence spending and investment decisions. In certain conditions – such as when the economy suffers a large contraction in demand – policymakers may want to respond by cutting real interest rates sharply, possibly below zero. While nominal interest rates cannot fall below zero, real ones can if inflation is positive. In fact, what really matters for the real rate of interest is not inflation itself but expected inflation – what consumers and companies think inflation will be in the future. With a negative output gap that is set to widen dramatically over the next year or two, the UK is likely to experience negative real interest rates very soon. But those negative real rates would not be possible without a positive inflation target, which can anchor expectations above zero.

Oddly enough, these two reasons are rarely considered together. But a business that is considering investment in new plant and machinery will calculate a rate of return that is not based on everyone else's sales, but their own. As such, the relevant turnover data for that firm are the quantities sold and prices charged that the business manages to achieve – not some upwardly biased inflation measure which averages across different companies. A positive inflation target is a good idea both because of measurement bias and the possible need for negative real rates – but perhaps those ideas should not just be considered independently.

Given the need for a positive inflation target, the obvious question is how high it should be. Strangely, there is relatively little evidence on this front. Most inflation 'crisis' studies, which examine the impact of past hyperinflationary episodes, tend not to be about countries with independent central banks and positive inflation targets. And most modern inflation 'models' tend to focus on deviations of inflation

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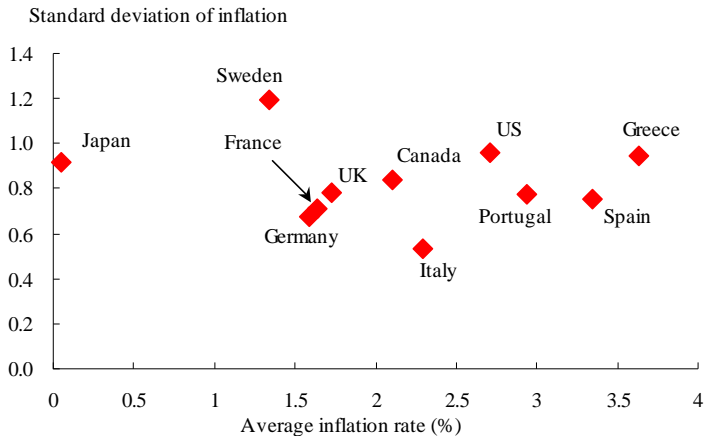
around its steady state, or target level, thereby ignoring the target itself completely.

There are two questions we can plausibly ask about what number the inflation target should be: what number is too high?; and what number is too low?.

The 'too high' answer can be surprisingly hard to pin down. Anyone who experienced the UK economy in the 1970s will attest that high inflation can be extremely volatile, which results in more uncertainty and hence short-termism, so 25% is out. Given that RPI inflation nudged 11% during the late-80s boom, many people would say that is too high too. But what is the difference between 2% inflation and, say, 3% or 4%?

One problem here is that we cannot really refer to our own experience prior to inflation targeting. Almost by definition, different inflation rates over time in the UK will reflect different monetary regimes. And in any event, the shocks hitting the economy at any one time will have been different. Instead, we have to look to other countries. This presents a problem – most advanced economies either have 2% inflation targets, or a reliance on commodities where oil price movements can drive headline inflation up or down a great deal. Thankfully other countries, and the euro area in particular, offer some insights. While Germany, France and Italy have all experienced low inflation and low inflation volatility, some of the other euro area countries have experienced higher inflation rates over the past ten years. But, at the same time, they have not seen any appreciable difference in inflation volatility (Chart 1). With an inflation targeting regime, it is possible to have 3% or 4% inflation and still enjoy low inflation volatility.

Chart 1: Inflation and inflation volatility (1997 - 2008) ^(a)



(a) Calculated from national CPIs.

Sources: National statistics offices and author's calculations.

So, what is the difference between 2% inflation and 4% on the upside? The answer is not very much.

What about the downside – what number is too low for an inflation target?

The key concern here is the desire to avoid negative inflation, or deflation. Deflation occurs when prices persistently fall from year to year. Is it not when individual prices fall, for example in the half price furniture sales that crop up all the time. Deflation is a general decline in a broad range of prices across the economy as a whole.

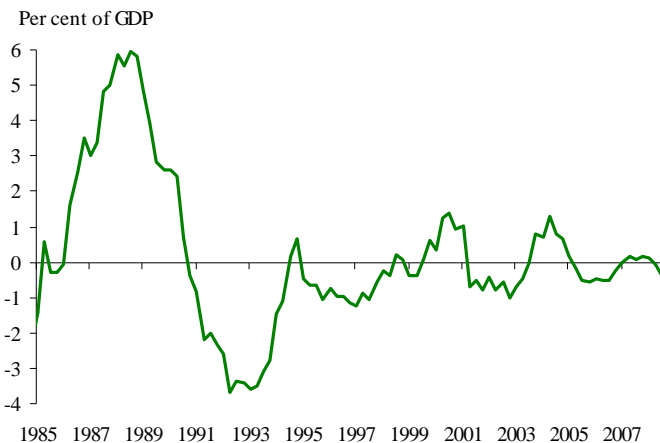
It has horrendous consequences. Deflation keeps the real interest rate positive, because the nominal interest rate cannot fall below zero and falling prices feed through to expectations. So monetary policy makers may be unable to get a real interest rate low enough to stimulate demand in the event of a sharp downturn. Deflation also discourages spending – since, if most goods and services will be cheaper next year, people will delay buying them. Perhaps most worryingly, deflation increases the real value of debt in the economy. Even if borrowers face low (or zero) nominal interest rates, when prices are falling the principal debt is increasing in real terms. For a heavily indebted economy like the UK, deflation

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would be a nightmare – and the problems debtors would face would have profound implications for the stability of the financial system. One glance at the Japanese economy over the past couple of decades shows how damaging deflation can be. Of course, Japan was also going through a banking crisis at the same time, which served to make matters that much worse. That would, er, never happen here.

So deflation should be avoided if at all possible. That means the inflation target should be a large enough buffer-zone above zero. Is 2% large enough? The events unfolding in the UK economy right now suggest not. Over the next two years, the UK economy will suffer a severe downturn, with output probably falling at least 2½% from peak to trough. Given that we started this recession with an output gap that was close to zero (Chart 2), a consequence of the MPC having been broadly successful at keeping demand and supply in balance, the output gap it is likely to be very large and very negative over the next year or so. Unlike previous recessions, we have not first had a boom to push demand above potential supply. A negative output gap of 4% is not remotely implausible. With headline CPI inflation already set to fall below 1% as commodity price falls feed through, and the Treasury itself expecting RPI inflation to turn negative in 2009, the UK economy could be flirting with deflation all too soon. A two per cent target will not prove to have been enough insurance this time around.

Chart 2: The UK output gap



Sources: ONS, Bank of England and author's calculations.

Fans of 2% will point out that the events unfolding at the moment are extreme – a pronounced spike in commodity prices, the biggest banking crisis since WW1, etc. But whereas day-to-day monetary policy can deal with these shocks by weighing up their likelihood on an 'expectational' basis – or in other words focusing on the average outcome of different upside and downside risks – the policy framework should not. The design of monetary policy, the institutional arrangements, should be more akin to a 'max-min' strategy – ensuring that, in the worst of possible circumstances, the best possible outcome is achieved. With some forecasters claiming oil and other commodity prices are likely to fluctuate even higher in the medium term, the shocks we have recently been hit by may become more common. We are about to find out that two per cent is not enough to provide sufficient protection against deflation: the first change in the inflation target should be to make it higher.

What price should we target?

So the current inflation target is probably too low. But if we are redesigning the policy remit, there is a bigger question that we should ask – what exactly should monetary policy target? Targeting inflation has worked pretty well for most of the past fifteen years. But what about the calls for the remit to take explicit account of other prices in the economy – such as asset prices? What is the right price to target?

In answering this question, we need to think about what monetary policy is actually designed to do. Low inflation is not an end in itself – but the stability and confidence it engenders is a definite boost to the economy as a whole. By keeping demand in balance with supply, monetary policy provides a nominal anchor – a reference point for the investment, hiring and pricing decisions that are made throughout the economy.

But why do we need monetary policy to do this? When a shock hits, there are two ways the economy can adjust: either prices change, or quantities do on the real side of the economy. If prices in the economy were fully flexible, then when demand fell, or productivity changed, firms would be able to adjust their prices (and their underlying production costs) straight away. As a result, output and employment would be unaffected unless their equilibrium levels changed. It is precisely because prices do not adjust straight away that a reduction in demand can lead to

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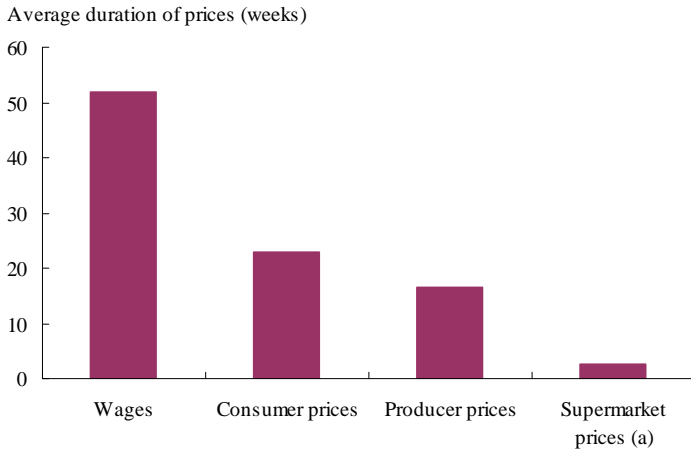
unemployment, and cuts in production. By keeping demand in line with supply, monetary policy can minimise the need for prices to change – and hence reduce the cost to the economy in terms of unemployment and lost output when the shocks hit.

This motivation offers insight to what monetary policy should focus on. Those markets where the real cost of shocks will be highest are those where prices are the most inflexible – where the nominal side of the economy takes a long time to adjust to shocks. In fact, the optimal index for monetary policy to focus on will be an index of the stickiest prices in the economy, as those markets with sticky prices will see the biggest changes in real variables when shocks hit, whereas flexible prices will be able to adjust quickly.

So monetary policy should target sticky prices. Which rules out asset prices. Quite apart from arguments about how big a change in rates might need to be in order to pop asset price bubbles, or how exactly you hit two or more objectives with a single policy instrument, policy should simply not be targeting those prices that respond very quickly to changes in the economy. Exchange rates, equities, yields – even house prices, compared to many consumer prices – tend to respond quickly to changes in the economy. Commodity prices are also out – providing a rationale for the various measures of 'core' inflation that exclude these volatile items. Including them can clearly distract policymakers.

So what prices should policy focus on? One thing to avoid is an overly complicated measure – a specific, esoteric index of prices that would be hard for people to understand. An easily recognised index would be preferable. There are two obvious candidates – prices in product markets, or prices in labour markets. In fact, evidence from micro data on prices and wages suggests that prices change far more frequently than wages (Chart 3). That means shocks to the economy will take longer to feed through the labour market than through the product market, and suggests that monetary policy has been looking at the wrong nominal variable.

Chart 3: Average duration of prices and wages



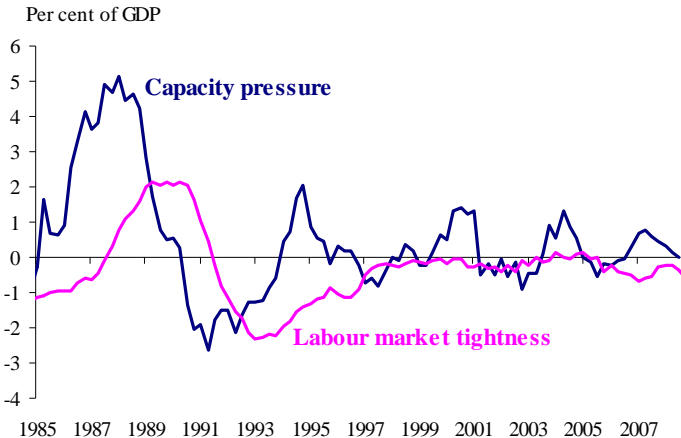
(a) Based on weekly data, other observations based on monthly data.

Sources: Bunn & Ellis (2009), Bank of England Quarterly Bulletin, forthcoming, and Forth & Millward (2000), NIESR Discussion Paper 173.

The output gap also offers some insights here. It is formally defined as the difference between demand and potential supply in the economy, and we can split this into these two markets as well. The difference between demand and current supply is capacity utilisation – the pressure firms are currently under to produce their output. That indicates disequilibrium in the product market, where goods and services are bought and sold. The difference between current supply and potential supply represents disequilibrium in the labour market. This is often gauged as the gap between the unemployment rate and the so-called NAIRU or, more correctly, the natural rate of unemployment. In fact, participation – the size of the labour market – also matters, as well as hours worked. Disequilibrium in either of the product or labour markets will show up in the output gap, and will only fade as prices and wages adjust.

Why We Should Change the Inflation Target

Chart 4: Capacity pressure and labour market tightness

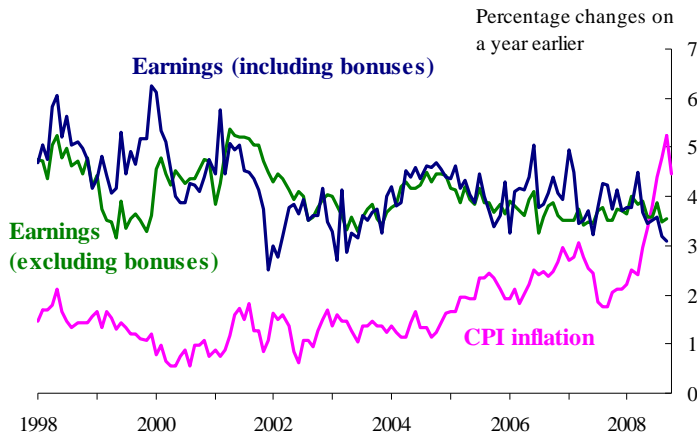


Sources: ONS, Bank of England and author's calculations.

These two measures of disequilibrium are shown in Chart 4. The difference between the two lines is fairly obvious. One point in particular is the variability in the two series. Capacity pressure is more volatile than tightness in the labour market – and also less persistent. When employment moves away from equilibrium, it can take a long time to get back there. In contrast, production gets back to capacity more quickly. But this is not surprising – it is entirely consistent with wages being less flexible than prices. Because wages take a long time to adjust, unemployment is higher or lower than equilibrium for a long time. But because prices take relatively less time to adjust, output gets back to trend more quickly. By acting to stabilise the labour market, rather than the product market, the MPC can minimise the disruption to the economy when shocks hit.

In truth, the MPC are unwittingly letting this scenario play out at the moment. The rise in oil prices – and indeed in the price of credit – is essentially an increase in costs for firms. In order to sustain output and employment at their natural levels, real wages must fall. The key question is whether inflation should be kept on target, and wage growth pushed below it – or whether wage growth should be held steady and price inflation should be allowed to overshoot. Where wages are more flexible than prices, inflation should be held steady while wages adjust. But when wages are stickier, we should let inflation overshoot – exactly what has happened in the UK this year (Chart 5).

Chart 5: Wage and price inflation



Source: ONS.

What other benefits would there be in moving to a wage inflation target? The key one would be to focus attention on what really matters in the economy. The ECB has been outspoken in its desire to see an end to wage-price indexation in the euro area – the automatic linking of wages with prices. If an economy is going to adjust swiftly to the shocks that hit it, real wage resistances like these should be abolished. The indexation problem is less widespread in the UK; but there is still an expectation in some quarters, particularly the remaining unions, that wages should have to rise as fast as prices. Explicitly targeting wage inflation would minimise this behaviour, and engender smaller distortions in output and employment. Large spikes in commodity prices would also not attract too much attention from the MPC, provided the wage target was credible. In fact, the MPC has inadvertently delivered more stable wage growth than price inflation over the past ten years – the variance of average earnings has been lower than that of either RPI or CPI inflation. But it is when the big shocks hit the economy that a clear understanding of what really matters is most important – and having policymakers focus on the labour market, rather than goods and services prices, would do that.

Conclusions

Over the past eleven years, the MPC has managed to deliver relatively stable growth

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and inflation. The credit crunch and unfolding recession have thrown the monetary arrangements back into the spotlight – with policymakers overly concerned about spikes in commodity prices earlier this year, and now subsequently facing the threat of deflation next year. The first test of the authorities will be to bring the UK through its current difficulties; the more important task is to ensure that these problems are avoided in the future. Raising the inflation target would provide more insurance against deflation at little cost to the economy; and targeting prices in the labour market, where nominal rigidities are more pronounced, would help policymakers to focus on what really matters, and avoid too much distraction from other factors like commodity prices. The MPC has done a good job so far, but this is the first time it has really been tested. Once the economy has come through its current difficulties, we should look again at what the institutional arrangements for monetary policy should be.



BANK OF ENGLAND

Working Paper No. 364

What lies beneath: what can disaggregated data tell us about the behaviour of prices?

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March 2009



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What lies beneath: what can disaggregated data tell us about the behaviour of prices?

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Abstract

This paper uses a factor-augmented vector autoregression technique to examine the role that macroeconomic and sector-specific factors play in UK price fluctuations at the aggregate and disaggregated levels. Macroeconomic factors are less important for disaggregated prices than aggregate ones. There also appears to be significant aggregation bias — the persistence of aggregate inflation series is much higher than the underlying persistence across the range of disaggregated price series. Our results suggest that monetary policy affects relative prices in the short to medium term, and that the degree of competition within industries plays a role in determining pricing behaviour.

Key words: Inflation persistence, disaggregation, principal components.

JEL classification: C3, D4, E31, E52.

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The views expressed in this paper are those of the authors, and not necessarily those of the Bank of England or the Monetary Policy Committee or Daiwa Securities SMBC. We are grateful to Alex Bowen, Stephen Millard, Miles Parker, Simon Price, Garry Young and an anonymous referee for useful comments. All mistakes remain our own. This paper was finalised on 25 November 2008.

The Bank of England's working paper series is externally refereed.

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Summary

How do prices respond to changes in interest rates? Most previous work has tried to answer this question by looking at aggregate price measures, such as the consumer prices index (CPI) or the National Accounts consumption deflator. This paper takes a different approach. Following recent work on US data, we examine the behaviour of both aggregate and disaggregated prices in the United Kingdom using a large volume of data covering prices, volumes, money and asset prices.

In this paper, we summarise these data by using ‘principal components’, or ‘factors’. Factor analysis uses linear transformations of data series to identify common components that underlie those series. The ‘factors’ are calculated by creating combinations of the underlying data series to make new series that in turn capture the largest possible amount of variation in the data set as a whole, while remaining statistically independent of each other. We then use these factors to estimate a simple model (known as a vector autoregression, or VAR), which in this case relates these factors to their previous values and the interest rate. The resulting model is known as a ‘factor-augmented vector autoregression’, or FAVAR for short.

The advantages of a FAVAR are that it encompasses a large number of data series but, at the same time, is relatively simple to estimate. By estimating a FAVAR on disaggregated data, we are able to examine how individual disaggregated prices respond to monetary policy and other macroeconomic shocks. The model also tells us how important these macroeconomic factors are, compared to sector-specific factors that affect the individual disaggregated series.

Our benchmark results match those of previous studies and suggest that aggregate demand falls before aggregate inflation when interest rates rise. However, our disaggregated results offer a number of insights that are not captured by aggregate models.

- First, while macroeconomic factors are very important for aggregate data such as CPI inflation, they are much less important for disaggregated inflation measures. Sector-specific factors are at least as important for disaggregated prices.
- Second, we find evidence of significant aggregation bias – aggregate inflation is far more closely related to its previous values than disaggregated inflation measures. This suggests that aggregate inflation measures do not offer a good guide to the behaviour of underlying prices. In other words, trying to infer the statistical properties of individual prices from those of aggregate price indices is likely to be misleading.
- Third, different disaggregated prices respond differently to changes in interest rates, suggesting that monetary policy can affect relative prices in the economy.
- Fourth, there is some evidence that competition within industries plays a role in determining how companies set prices – in particular, companies in less competitive industries may be more able to pass on changes in prices to customers.

1 Introduction

UK monetary policy is concerned with keeping inflation on target at 2% a year. So it is important for policymakers to consider how prices behave: without a good understanding of pricing behaviour, not least how prices respond to monetary policy, policymakers may struggle to achieve price stability.

One common feature of many economic models is some form of ‘price stickiness’. Numerous theoretical mechanisms have been proposed to underpin this assumption, including costs of adjusting prices (Rotemberg (1982), Mankiw (1985)), staggered contracts (Taylor (1980)), threshold pricing (Sheshinski and Weiss (1977)), and fixed probabilities of being able to change prices (Calvo (1983)).⁽¹⁾ One popular pricing model that results from the last approach is the so-called New Keynesian Phillips Curve (NKPC). Previous estimates of this model imply that on average, firms change their prices every five to six quarters (Gali and Gertler (1999)), although some studies suggest once every two years (Smets and Wouters (2003)).

The estimates reported above are based on aggregate data and exceed the timings reported in direct surveys of companies’ price-setting behaviour. For example, Blinder *et al* (1998) and Druant *et al* (2005) both find that the median price changes once a year in the United States and the euro area, respectively. Recent studies, also based on disaggregated data, suggest that individual prices may be even more flexible than this. In particular, Amirault *et al* (2005) and Bils and Klenow (2004) found that prices change on average every three to four months.⁽²⁾ And evidence from 300 of the Bank of England’s Agency contacts suggests that half of companies change prices at least five times a year (Bank of England (2006)).

A useful first step in trying to understand the discrepancies between macro and micro-data based estimates would be to analyse the behaviour of aggregate and disaggregated prices in a single, consistent framework. Boivin, Giannoni and Mihov (2007, hereafter BGM) have recently demonstrated how this can be done using US data. Their innovative approach uses the factor-augmented vector autoregression (FAVAR) methodology developed by Bernanke, Boivin and Elias (2005, hereafter BBE) and allows large amounts of data to be incorporated into the estimates (in contrast to most standard economic models). Apart from providing evidence on whether aggregate price measures accurately represent individual (sectoral) pricing behaviour, the FAVAR methodology makes it possible to differentiate between price changes that reflect common, or macroeconomic, factors, and sector-specific concerns. Accordingly, it might also be helpful in trying to account for the considerable heterogeneity among companies and sectors found in different direct studies of price-setting.

In this paper, we follow BGM’s approach for the United Kingdom, using disaggregated consumer expenditure data. However, we also identify a model using sign restrictions as well as the Cholesky method, following recent work on VARs. In common with BGM’s US results, we find that

⁽¹⁾ By themselves, these sticky price mechanisms do not typically capture the persistence in aggregate inflation (Lendvai (2006)), and *ad hoc* adjustments are typically added to improve the fit of the model.

⁽²⁾ Allowing for sales and special promotions, Nakamura and Steinsson (2007) find the median duration of retail prices is between eight and eleven months.

disaggregated price series exhibit less persistence than aggregate measures would imply, and that sector-specific factors are important for determining fluctuations in disaggregated prices. Our results suggest that monetary policy affects relative prices in the short to medium term, and that the degree of competition in sectors is significantly correlated with the behaviour of prices.

The rest of this paper is structured as follows. Section 2 sets out the methodological approach used, and describes the data set. Section 3 presents results from this approach for aggregate variables. Section 4 then presents results using the disaggregated consumer expenditure data, and Section 5 looks at how these results relate to other sectoral information. Section 6 concludes.

2 Methodology

The FAVAR approach pioneered by BBE assumes that there are a number of common factors that affect all variables in the economy: the economy itself is measured as a large data set X_t that contains many different series. The common factors or components, C_t , may reflect underlying economic conditions such as ‘activity’ or ‘pricing pressure’. They are estimated as the first K principal components of X_t . These components, or factors, then form the variables that are included in an estimated VAR model. From the resulting VAR estimates, responses for the original data series can be derived from the eigenvectors associated with the (common) principal components.⁽³⁾

One important issue with all VAR models is how to identify economic shocks. BGM identify monetary policy by explicitly including the policy rate (ie the Federal funds rate), R_t , as one of the common factors (see also Boivin, Giannoni and Mihov (2007) for more details). They then order the Federal funds rate last, and treat its innovations as monetary policy ‘shocks’, ie effectively, they use the Cholesky identification method. This method, however, has been criticised by a number of authors, including Canova and de Nicolo (2002) and Uhlig (2005) on the grounds that it may be more stringent than is borne out by the data. As a less restrictive alternative, those authors propose an identification system based on sign restrictions. In essence, sign restrictions force the initial response of individual variables to be either positive or negative, but impose no assumptions on the adjustment path that follows (see also Uhlig (2005) for more details on this identification method).

In order to use sign restriction based identification, we must place some interpretation on the principal components in the VAR.⁽⁴⁾ To allow us to do so, we partitioned the data set of macro variables into different categories, grouping activity, price, money and asset price variables separately. By taking principal components from the resulting partitions of the data set, we could retrieve common components that were plausibly interpretable as ‘activity’ or ‘price’ factors. In other words, we interpret the first principal component of the collection of activity factors as an ‘activity’ factor, etc. This then allows us to use sign restrictions to identify the VAR, and compare it with BGM’s original Cholesky identification method.

Technically, our model can be represented by the following two equations

⁽³⁾ More information on the FAVAR approach is available in BBE. The authors also describe an alternative implementation method, which is a single-step Bayesian likelihood approach. For simplicity, we follow the two-step principal components approach. Stock and Watson (2005) explore how many factors should be included in the VAR.

⁽⁴⁾ For example, the assumption that activity initially falls in response to a negative demand shock requires us to identify one of the common components as an ‘activity’ variable.

$$\begin{pmatrix} Y_{1,t} \\ Y_{2,t} \\ \cdot \\ \cdot \\ R_t \end{pmatrix} = \begin{pmatrix} B_{11} & \cdot & \cdot & \cdot & B_{1N} \\ B_{12} & \cdot & & & \\ \cdot & & \cdot & & \\ \cdot & & & & B_{NN} \\ 0 & 0 & \cdot & \cdot & 1 \end{pmatrix} \begin{pmatrix} F_{1,t} \\ \cdot \\ \cdot \\ F_{N,t} \\ R_t \end{pmatrix} + \begin{pmatrix} v_{1,t} \\ \cdot \\ \cdot \\ v_{N,t} \\ 0 \end{pmatrix}$$

$$Z_t = c + \sum_{j=1}^L \rho_j Z_{t-j} + \varepsilon_t$$

where $Z_t = \{F_{1,t}, \dots, F_{N,t}, R_t\}$. Here, $Y_{1,t}, \dots, Y_{N,t}$ represent portions of our data set corresponding to different macroeconomic variables. For example, $Y_{1,t}$ gathers together all our data on real activity, $Y_{2,t}$ contains inflation, etc. $F_{1,t}, \dots, F_{N,t}$ denote the unobserved factors that are extracted from this data set, while $B_{i,i}$ represent (blocks) of factor loadings. R_t denotes the policy rate, which we treat as an observed factor.

As mentioned above, we extract the factors in two ways. In our benchmark model, we assume that the factor loading matrix is full. That is, we extract N factors from the entire data set without considering the different blocks of data separately. Our alternative model imposes the restriction that the off-diagonal elements of the factor loading matrix equal zero. In other words, the factors are extracted from blocks of the data corresponding to real activity, inflation, money and asset prices.

We use the principal component estimator employed by BBE to extract the factors. Note that the estimator incorporates the normalisation that $B'B = I$. This is required because the principal components are subject to rotational indeterminacy and are econometrically unidentified.

The dynamics of the factors and the policy rate are described by a VAR shown in the second equation above. We estimate the model in two steps, using the principal component estimates of the factors obtained in the first step. As the number of endogenous variables in our model is quite high, we use a Bayesian estimator. This allows us to incorporate inexact prior restrictions described in Sims and Zha (1998) into the analysis: in particular, our inexact prior restriction was that the variables followed a first-order autoregressive process. We approximate the posterior distribution using Gibbs sampling. Details on the conditional posterior distributions are available in Uhlig (2005).

2.1 Data

Our data set comprised around 60 macroeconomic UK data series, running from 1977 Q1 to 2006 Q3. It included activity measures such as GDP, consumption and industrial production, various price measures including RPI, CPI and the GDP deflator, as well as money and asset price data. Where appropriate, variables were log-differenced to induce stationarity. In addition to these macro variables, we included a large number of disaggregated deflator and volume series for consumers' expenditure. The Office for National Statistics (ONS) publishes over 140 subcategories of

consumer expenditure data in value, volume and deflator terms, going back to the 1960s.⁽⁵⁾ This gives us a ready-made collection of consistent disaggregated price (and volume) data over a long time period.

3 Results: aggregate variables

Before examining the response of disaggregated price series, we estimated ‘baseline’ models for the UK macroeconomy. The first of these was a standard five-variable VAR, with CPI inflation, GDP growth, M4 growth, the UK sterling exchange rate index (ERI) and Bank Rate.⁽⁶⁾ This basic VAR model offers a benchmark to compare our later FAVAR models to. Chart 1 shows impulse responses of the five variables in this VAR to a monetary policy contraction.⁽⁷⁾ As is the case with several other VAR models, our responses suggest that GDP and M4 growth fall after the policy contraction, but also that CPI inflation *rises* after the monetary policy shock. This is the well documented ‘price puzzle’ pointed out by Sims (1992).

The second model we estimated was a FAVAR. Here, we followed BGM’s identification approach and explicitly identified monetary policy shocks. The model contained eight factors (plus the monetary policy variable, R_t).⁽⁸⁾ Chart 2 shows the resulting impulse responses for CPI inflation, GDP growth and other variables in this model to a 100 basis point (bp) rise in Bank Rate.

Some features of the responses are worth highlighting.⁽⁹⁾

- First, median CPI rises following a monetary policy contraction. While not statistically significant, this is in contrast to BGM, who do not find such a price puzzle in their aggregate responses. Since recent work suggests that this ‘puzzle’ may actually reflect a misspecification of the underlying VAR model (Giordani (2004), Castelnuovo and Surico (2006)) this could indicate that our set-up is not free of similar problems.
- Second, the median response suggests that CPI inflation starts to fall (relative to the counterfactual of no policy innovation) almost two years after the initial policy shock. This ‘delayed response’ of inflation is not uncommon in other models. But it is somewhat longer than other large models of the UK economy: for example, using a large structural macro model Harrison *et al* (2005) find that the maximum impact of interest rates on CPI inflation occurs between one and two years after the interest rate shock.⁽¹⁰⁾

Taken together, these features suggest we may want to verify the robustness of our findings and consider alternative versions of the model. In the light of external concerns about BBE’s

⁽⁵⁾ See ONS (2007).

⁽⁶⁾ Unless otherwise stated, all the results in this paper are based on models with two lags: (quarterly) growth rates are calculated as log differences.

⁽⁷⁾ The model is identified using a standard Cholesky ordering. This VAR (and the other FAVAR models) was estimated using Bayesian techniques, which are used to derive the standard errors. In all instances, little weight was imposed on the simple autoregressive priors. One standard error bands are shown in red throughout this paper.

⁽⁸⁾ This is broadly in line with Stock and Watson (2005) who find that seven factors are appropriate for modelling the US economy. Our results support this view: adding further factors had little impact on our results.

⁽⁹⁾ Chart 3 shows the underlying factors used in this FAVAR.

⁽¹⁰⁾ In other words, the trough in the impulse response should occur at around two years, rather than the response finally becoming negative at that point. The estimated impulse response troughs almost four years after the policy change, which is also significantly higher than stated Bank priors of around a year.

identification scheme, expressed for example in Stock and Watson (2005), we estimated another FAVAR where shocks were identified using sign restrictions, rather than Cholesky ordering.

As mentioned in the methodology section, in order to identify the model using sign restrictions, we need to place some economic interpretation on the factors. As such, it is appropriate to present them for scrutiny. Chart 4 shows the four key principal components from the partitioned macro data set,⁽¹¹⁾ where we grouped variables into four categories: activity; prices; money; and asset prices. While volatile, the ‘activity’ factor closely corresponds to cyclical estimates for the UK economy (Ellis and Turnbull (2007)), the ‘inflation’ factor resembles key price variables such as CPI and RPI while the ‘asset price’ factor is reminiscent of interest rate data.⁽¹²⁾

In identifying the model, we imposed the sign restrictions on the model based on three types of shocks: demand, supply, and monetary policy. The sign restrictions force the initial responses of the FAVAR variables to be either positive or negative. Our restrictions were chosen to match standard theoretical prior beliefs from DSGE models – for example, in response to a positive supply shock, we imposed that output would rise in the first instance, and inflation fall. The full set of identifying restrictions we used is presented in Table A.⁽¹³⁾

Chart 5 shows the impulse responses of macro variables to a 100bp rise in this alternative FAVAR model. Now, the largest impact on CPI inflation occurs around two years after the shock. Similarly, the biggest impact on GDP is after a year or so, consistent with Bank of England (2004).⁽¹⁴⁾ While this model appears more consistent with previous Bank work, it is important not to overplay the differences between the two sets of results. Both models find that output falls, and then inflation, in response to a monetary policy shock. Both models find that the impact of monetary policy on aggregate inflation is temporary, with inflation returning to base over time. These consistencies lend support to both identification methods.

One advantage the sign-restriction model offers is the ability to analyse the impact of other shocks that hit the economy, not just changes in monetary policy. Chart 6 shows responses of macro variables to a supply shock – an unexpected decrease in productive capacity. As we might expect, inflation rises in response, while activity falls in the short term. Chart 7 shows responses to a demand shock – an unexpected rise in demand. Once again, our sign-restriction model fits standard theoretical priors well.

Our 30-year data period covers a number of changes in the UK economy – most noticeably, in a policy context, the shift to inflation targeting in 1993. Accordingly, before examining disaggregated data, as a final robustness check, we tested for the presence of a structural break in our model. To examine whether the policy responses were affected, we estimated a version of the Cholesky model with a dummy variable from 1993 onwards. The results are shown in Chart 8.

⁽¹¹⁾ That is, those principal components that we placed the sign restrictions on to identify the VAR.

⁽¹²⁾ It is worth noting that we included a total of ten factors in the sign-restriction FAVAR. This included four inflation and four activity factors. Due to the partitioning, disaggregated price and quantity results (presented later) will be based only on those pricing and activity factors included in the model. As such, we wanted to include more than one factor, to try to capture a greater degree of variance in the disaggregated series.

⁽¹³⁾ By construction there is no ‘price puzzle’ here in our ‘pricing’ factor, as it is constrained to fall following a contractionary monetary policy shock.

⁽¹⁴⁾ In the next section, we explore the differences between the Cholesky and sign-restriction models in more detail.

Although the standard errors are larger for estimates from 1993 onwards, as we would expect given the smaller amount of data, the median impulse responses are very similar, giving us increased confidence in the robustness of our findings.

So, in summary, we have two FAVAR models with which to examine the behaviour of disaggregated prices. In the following sections, we compare the results from both.

4 Results: disaggregated prices

Having established our baseline FAVAR models, we then examined the dynamics of the disaggregated consumer expenditure data. In total, we included over 140 different expenditure categories.⁽¹⁵⁾ Chart 9 plots the response of the aggregate consumption deflator (red) and the individual disaggregated deflators (blues) to a contractionary monetary policy shock in our Cholesky FAVAR. (Charts 10-11 plot the corresponding responses for the individual price levels.) Chart 12 plots the inflation and price-level responses in our sign-restriction FAVAR (individual disaggregated responses are shown in Charts 13-14).

Overall, the two sets of model results are broadly consistent – for example they both exhibit a range of responses among the disaggregated prices, in terms of magnitude and speed. Both models suggest that some disaggregated prices respond swiftly to the contractionary monetary policy shock – and many inflation rates move quickly as well. At the same time, both models imply that some disaggregated prices take a little longer to respond, in line with BGM’s finding that some disaggregated US prices took six months to respond.

But there are also some differences between the two sets of model results – in particular the range of the disaggregated impulse responses in each model, where responses in the sign-restriction model are more marked than those in the Cholesky one.⁽¹⁶⁾ The model identification method appears to be very important for gauging the spread of disaggregated price responses. In part, this could reflect the fact that responses in the Cholesky model are based on all of the eight macro factors, whereas responses in the sign-restriction version are based on the four factors from the relevant data partitions.

In order to try and find the factors responsible for differences between both sets of results, we experimented with a variety of changes. Charts 9 and 12 are both based on FAVARs estimated over the whole data sample, and each model has two lags, so the underlying data cannot account for the differences. When we expanded the sign-restriction model, so that there were eight factors in the output and price partitions, the different results remained: so this does not appear to be the driving factor. Finally, when we attempted to estimate a model by placing sign restrictions on the Cholesky factors (Chart 3), we retrieved impulse responses with a wider range than was present

⁽¹⁵⁾ Some of these categories were subindices of the underlying series, but most were the highest level of disaggregation that was readily available.

⁽¹⁶⁾ Another difference relates to price puzzles: there is some evidence of price puzzles in the disaggregated data using the Cholesky approach, in relative contrast to evidence from the sign-restriction FAVAR. But this is unsurprising, given our identification methods and the associated responses of aggregate inflation. The lack of a generalised price puzzle is consistent with BGM’s results.

when those factors were modelled using the Cholesky identification method. This suggests that the different identification methods do account for the difference in the range of the impulse responses. We take some comfort from the fact that Peersman (2005) also compares a sign-restriction model to a model with traditional restrictions, and finds similar results, in that the maximum impact of a monetary policy shock is larger in the sign-restriction model.

The impulse responses also tell us about how different prices respond. In particular, they show that a monetary policy shock has an impact on the relative prices of different goods and services – some prices are little affected (the cumulative response is close to zero) while others are more markedly affected (the cumulative response is large and persistent). At first sight this may seem counterintuitive. But it is worth remembering that our shock is not a ‘pure’ monetary shock in the sense of an exogenous decrease in the money supply. An increase in interest rates can reduce demand via different channels. One channel is via the reallocation of income from interest-paying debtors to interest-receiving creditors. If debtors and creditors have different preferences for spending on ranges of goods and services,⁽¹⁷⁾ then this reallocation of income could have a persistent impact on relative prices.⁽¹⁸⁾ Despite these changes in relative prices, the long-run impact of policy on aggregate consumption is broadly neutral, as we might expect.

One interesting question is whether the relative price changes are significant or not. To investigate this, we examined whether the response of individual price changes was significantly different from average inflation. Using a benchmark 10% significance level, we would expect 10% of sectoral prices to be different at any given time. Charts 15 and 16 show the proportion of sectors where individual sectors exhibit significantly different inflation from the average. The results do vary across the two models, but the consistent finding is that although there are some significant relative price effects in the short to medium term, there is no evidence of significant effects in the long run.

Our sign-restriction model also lets us examine the disaggregated responses of prices and volumes to demand and supply shocks. These responses are shown in Charts 17 and 18. As with the monetary policy shock, there is considerable heterogeneity among the disaggregated responses. One interesting feature of both sets of responses is that (aggregate and disaggregate) prices respond by more than volumes to all three shocks (monetary policy, supply and demand).

In addition to these dispersed impulse responses, we can use the FAVAR to examine the roles that macro factors play – measured here using our principal components – as well as sector-specific factors, measured using residuals. In other words, the FAVAR allows us to analyse the extent to which (sectoral) inflation rates reflect either macroeconomic or sectoral developments.

Tables B and C report summary statistics on the volatility and persistence of both aggregate and disaggregated quarterly inflation series for our two FAVAR models.⁽¹⁹⁾ In line with BGM’s results, we find that the majority of the volatility in aggregate inflation rates is due to fluctuations in the

⁽¹⁷⁾ This could follow if consumption preferences change with age, as younger people tend to have higher debts than older people: see Waldron and Young (2006).

⁽¹⁸⁾ An alternative channel is via changes in interest rates affecting the user cost of durable goods: see Power (2004).

⁽¹⁹⁾ These tables correspond to Table 1 in BGM.

common components (the exception being wages, where sector-specific factors matter more). However, for disaggregated inflation measures this is not true – for many disaggregated series, volatility is more commonly due to sector-specific factors, rather than the common macroeconomic factors. Unsurprisingly, there is considerable heterogeneity among the disaggregated series. Encouragingly, the results are very similar across both models, suggesting they are robust to the choice of identification scheme.

There is also a marked difference in the persistence of the series. We assessed this by estimating AR(1) models for each inflation series and their components, namely the common factors and the sector-specific components. In common with BGM, we found that the aggregate inflation measure exhibited a high degree of persistence, but that the disaggregated series exhibited far less persistence.⁽²⁰⁾

This difference between estimates of persistence at the aggregate and disaggregate level is marked – the persistence of the aggregate consumption deflator is not the average persistence of the underlying component series. This might partly reflect individual weightings in the consumption basket, which we have not explicitly taken account of here. But aggregation bias also plays a crucial role. As Imbs *et al* (2005) demonstrate in a PPP context, aggregate measures of persistence will be biased when there is heterogeneity in persistence among the disaggregated components. In particular, aggregate estimates of persistence will be biased upwards, ie will be higher than the average persistence of the underlying disaggregated series.⁽²¹⁾ Mojon *et al* (2007) find very similar results to ours for euro-area prices: fast adjustment in disaggregated series sits alongside slow adjustment at the aggregate level. They conclude that aggregation explains a fair amount of aggregate inflation persistence.⁽²²⁾

The same thing is happening here – the persistence of aggregate inflation is biased upwards, rather than simply being an average of the underlying series' individual persistence. Importantly, this means that using an aggregate inflation measure to gauge the typical behaviour of prices or price-setting at the microeconomic level might be misleading, as disaggregated prices do not behave the same way as aggregate indices. This in turn has implications for micro-founded models that characterise micro-behaviour based on aggregate inflation measures.⁽²³⁾

Interestingly, there is little evidence that sector-specific factors were important in determining persistence, for either aggregate or disaggregated series. What persistence is present is driven by the common macro components – and the fact that these are less important for disaggregated prices than aggregate ones is consistent with disaggregated prices exhibiting less persistence overall. This suggests that any persistence in prices is driven by persistence in the macroeconomy, such as

⁽²⁰⁾ For example, the AR(1) for the aggregate consumption deflator was 0.770, but the AR(1) for the median disaggregated series was 0.304.

⁽²¹⁾ This is in contrast to some other mechanisms, where sticky prices at the micro level can still be consistent with flexible prices at the macro level (Caplin and Spulber (1987)).

⁽²²⁾ Imbs *et al* (2007) introduce heterogeneity in price-setting behaviour across industries, and find that homogeneous models overestimate the apparent backward-looking behaviour in prices.

⁽²³⁾ Aoki (2001) argues that the optimal price index policymakers should target would place more weight on the prices that are sticky, and less weight on the prices that are more flexible. The fact that the persistence of aggregate inflation measures are biased upwards suggests that, implicitly, targeting an aggregate inflation measure may (partially) account for this.

activity or policy, and that sector-specific shocks are transitory in nature. This is consistent with sector-specific shocks playing little role at the aggregate level.

So, in summary, disaggregated inflation rates are significantly less persistent than aggregate measures, reflecting the role of aggregation bias. Disaggregated price changes are not very sticky. In addition, sector-specific factors are just as important for disaggregated prices as macroeconomic developments. In the next section, we examine whether these sector-specific factors are related to other sectoral characteristics.

5 The role of sectoral characteristics

The behaviour of disaggregated prices depends more on sector-specific factors than on macroeconomic developments. But can we say anything about how those sector-specific factors relate to sectoral characteristics? One simple test is to examine the relationship between the disaggregated impulse responses to a monetary policy shock and the estimated role that sector-specific factors play – as characterised by the volatility and persistence of sector-specific components in Tables B and C.

Table D presents correlations between these data.⁽²⁴⁾ There is evidence of a positive correlation between the variance of sector-specific factors and the response to monetary policy of sectoral prices. But, as our responses are to a contractionary monetary shock, this implies that companies who face larger sectoral shocks respond less (ie their response is more positive) to policy. This is consistent with both the state dependent pricing literature (see eg Dotsey *et al* (1997)) and the rational inattention literature pioneered by Sims (2003) and further developed by Reis (2006) and Mackowiak and Wiederholt (2007). The latter suggests that in the face of higher idiosyncratic volatility, relatively more attention should be put on idiosyncratic shocks than monetary policy shocks and hence the speed of response of the latter should be small (in line with the correlation we find). On the other hand, the result appears to contrast with the findings of Gertler and Leahy (2006), which suggest that the more companies are affected by idiosyncratic shocks, the more they adjust prices to a monetary policy shock.

We can also compare results from the model to other sectoral information, such as competition measures. In particular, we gathered four pieces of sectoral data, based on Supply-Use tables and other published work: the gross profit share; the ratio of imports to gross output; and two concentration ratios,⁽²⁵⁾ taken from Mahajan (2006). These data are available on an industry basis, rather than a disaggregated product basis – so we had to match the relevant disaggregated price series to the industry data. In some cases this was straightforward, but occasionally rather heroic assumptions were required. In total, we matched about 50 different disaggregated prices to our industry-level ‘competition’ measures.

Table E reports correlations between these four industry measures and sector-specific results from our two FAVAR models, namely: accumulated impulse responses to monetary policy shocks;

⁽²⁴⁾ Chart 19 plots the ten-quarter response against sector-specific variance for the sign-restriction FAVAR.

⁽²⁵⁾ Output of the largest 5% and largest 15% of businesses as a percentage of total sectoral output.

sector-specific variances; and sector-specific persistence. There is some evidence of significant correlations between impulse responses and sectoral characteristics. However, this evidence is not robust to model identification, reflecting the fact that disaggregated impulse responses in the two models are not always very similar.

However, there is a robust positive correlation between the size of sector specific fluctuations and the concentration ratio. This is consistent with sector-specific shocks having bigger effects in less competitive industries – perhaps because less competition allows companies to pass on changes in price more easily. In contrast, more competitive sectors may be unable to adjust their prices as easily (in a similar way to the correlation with monetary policy responses).

The other correlations that are common to both models relate to the persistence of sector-specific shocks. The profit share is positively correlated with this persistence – implying that sectoral shocks last longer in sectors with larger margins. In contrast, the import share is negatively correlated with sector-specific persistence. One interpretation of this result is that a higher import share implies greater competition (from overseas) – and hence that domestic producers find it harder to make persistent price changes in response to (domestic) sectoral shocks, for example because their foreign competitors do not face the same (sector-specific) shocks. The same logic could apply to the positive margin/persistence correlation, if higher margins are synonymous with less competition, and hence companies find it easier to make price changes persistent in response to sector-specific factors.

This evidence suggests that sector characteristics may be important in determining how different prices behave. Companies in less competitive industries may have more power over changing their prices, and making those changes more persistent. But companies in more competitive industries may find it hard to pass the impact of either sector-specific or macroeconomic shocks on to customers by changing prices.

5.1 Implications for monetary policy

Our results have a number of implications for monetary policy makers. First, and most obviously, BBE's FAVAR framework allows policymakers to combine the relative simplicity of VARs with the desire to include many different series. Furthermore, these models appear to fit policymaker's prior beliefs reasonably well, as judged by impulse responses: our results confirm that policy is felt first by activity at the aggregate level, rather than prices.

Our results also suggest that there may be less persistence in individual prices than is suggested by aggregate data. Average persistence among the disaggregated price series is much lower than is evident in the headline series, reflecting aggregation bias. This means that there may be relatively more flexibility in the nominal side of the economy than is evident from aggregate inflation – consistent with our finding that aggregate (and disaggregate) consumption volumes respond less to demand and supply shocks than consumption prices.

Our findings can also be compared with implications from various pricing theories. There are two key results that are particularly relevant: first, that sectoral effects on prices are important and

relatively short-lived, while macroeconomic effects are more long-lived; and second, that sectors facing larger idiosyncratic shocks respond less to monetary policy.

These results are inconsistent with the implications from time-dependent sticky-price models. In these models, the source of the shock should not affect the persistence the price response – and hence those time-dependent theories are inconsistent with the different persistence of the sector-specific and macro effects. In the same vein, by themselves time-dependent models do not allow different responses to policy shocks across sectors.

This suggests that, if policymakers want to capture economic relationships accurately, state-dependent rigidities should form the underlying basis of nominal frictions in their models. Of these, some forms of rigidity may be less appropriate than others – for example, menu costs would not allow for the different persistence of idiosyncratic and macro effects, while rational inattention models allow for this possibility. More work is required to examine which theoretical structures match the facts we have uncovered.

6 Conclusions

This paper has examined how aggregate and disaggregated price data respond to both macroeconomic and sector-specific developments in the UK economy. We have employed factor-augmented vector autoregression techniques to characterise the behaviour of the UK economy over the past 30 years, experimenting with two different identification strategies. Our results show that aggregate prices series are more persistent than the majority of the underlying disaggregated series, consistent with evidence of aggregation bias in a number of other studies. In short, aggregate inflation measures do not offer a good guide to underlying pricing behaviour or, in other words, trying to infer the statistical properties of individual prices from those of aggregate price indices is likely to be misleading.

Our results also suggest that what persistence is present in disaggregated prices reflects persistence in macroeconomic developments, rather than sector-specific factors. Disaggregated prices respond reasonably quickly to monetary policy changes, and few exhibit evidence of ‘price puzzles’, although there is considerable heterogeneity among those prices. One observation from the disaggregated responses is that monetary policy has an impact on relative prices in the short to medium term. Finally, we examine pricing behaviour across sectors, and find that competition within industries is significantly correlated with the behaviour of industry prices.

Appendix: Charts and tables

Chart 1: Impulse responses to a monetary contraction in a five-variable VAR

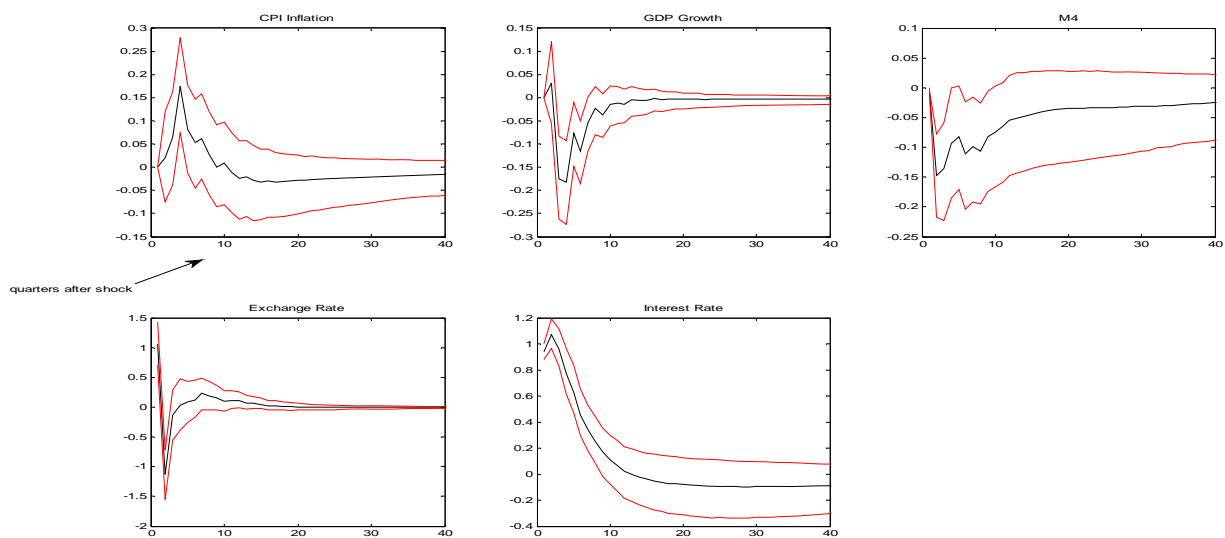


Chart 2: Impulse responses of key variables to a monetary contraction ('Cholesky' FAVAR)

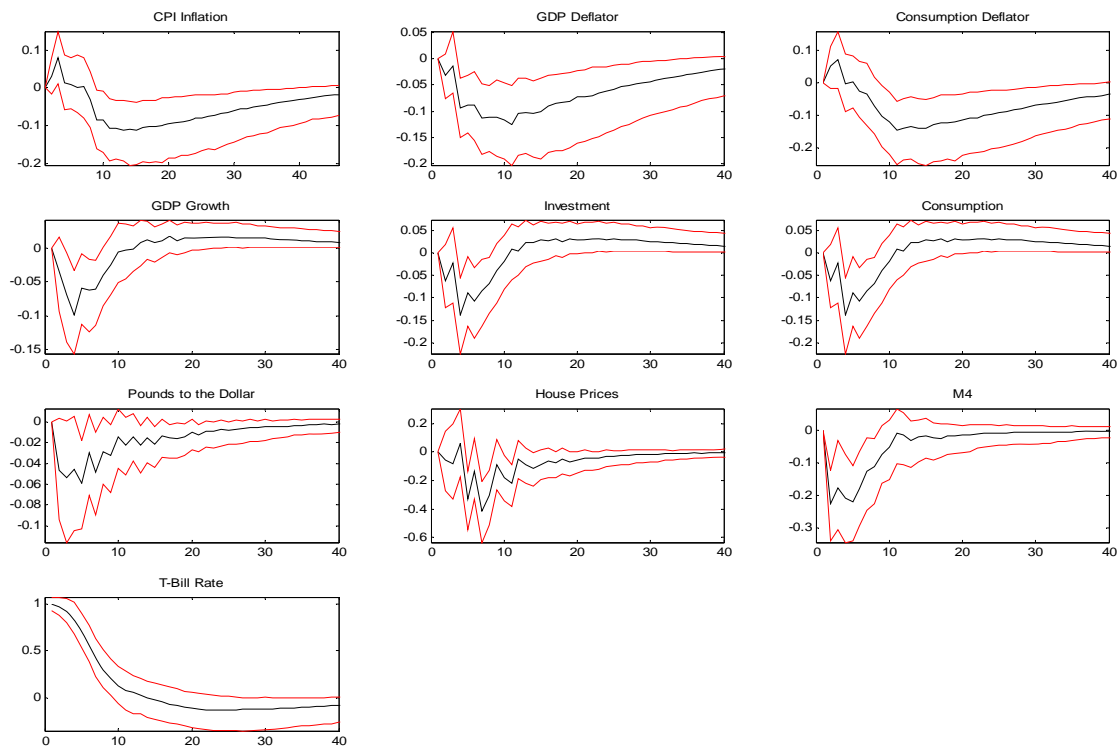


Chart 3: Factors in ‘Cholesky’ FAVAR

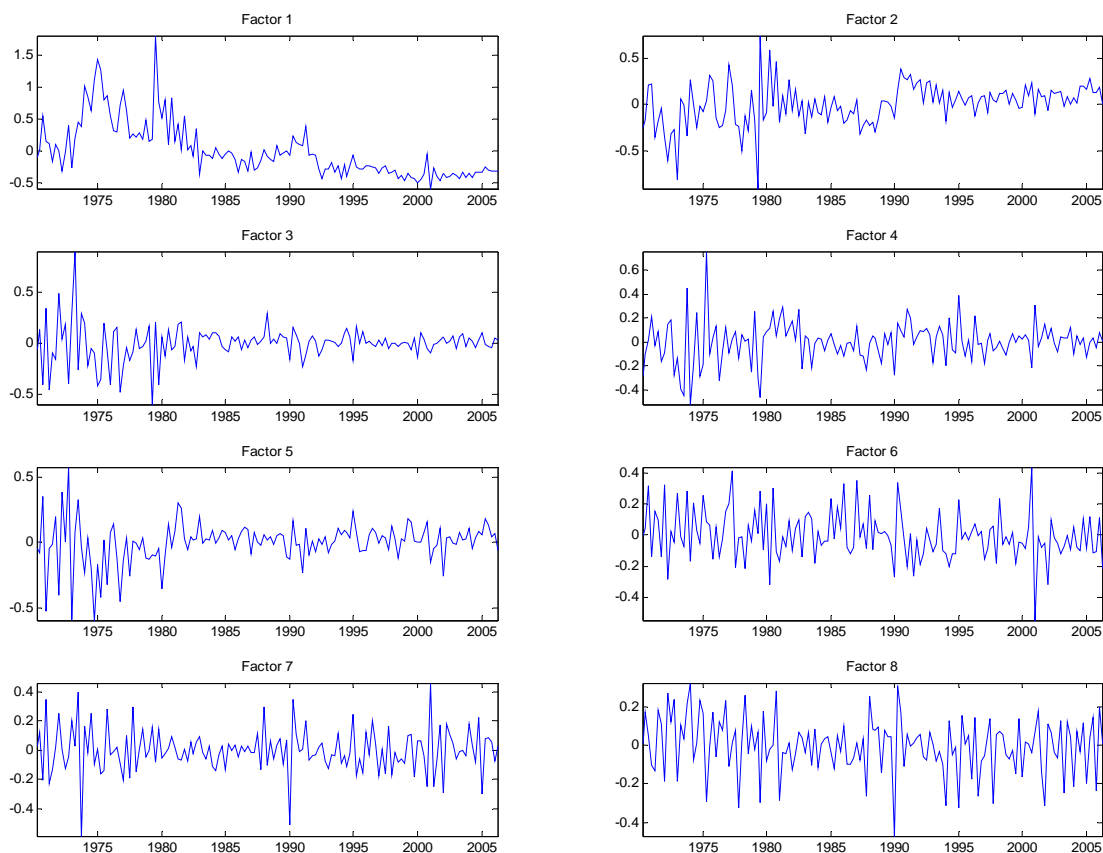


Chart 4: Factors in ‘sign-restriction’ FAVAR

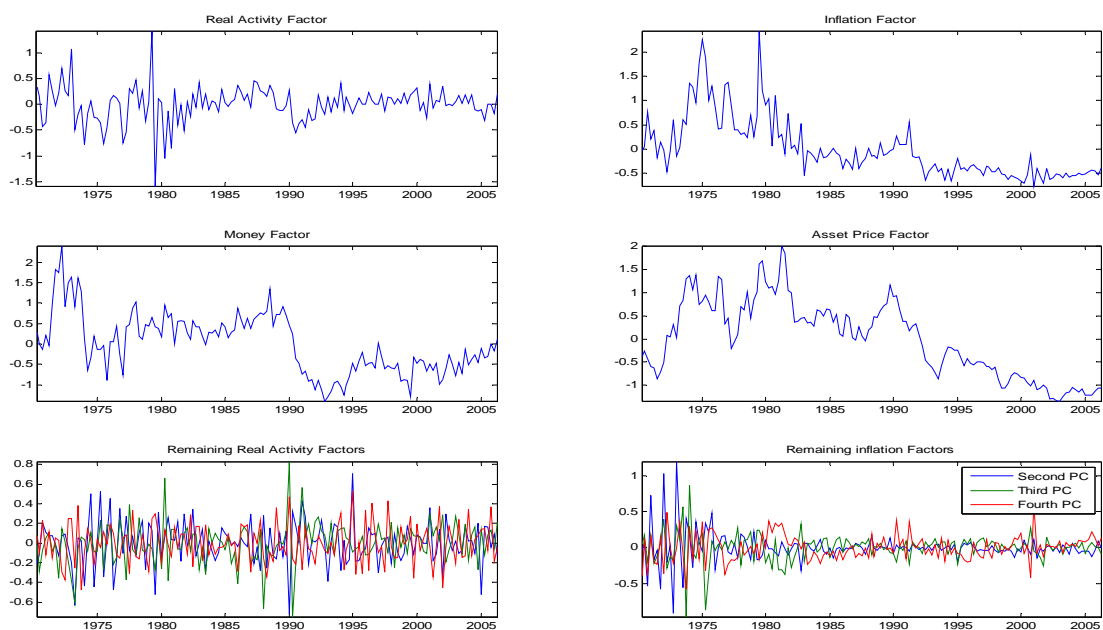


Table A: Sign restrictions used to identify FAVAR^(a)

	Demand shock	Supply shock	Monetary policy shock
Output factor	+	+	-
Inflation factor	+	-	-
Money factor	+	<i>n.a.</i>	-
Asset price factor	+	<i>n.a.</i>	-
Interest rate	+	<i>n.a.</i>	+

(a) Shocks correspond to increases in variables, eg an increase in demand, an increase in monetary policy rates.

Chart 5: Impulse responses of key variables to a monetary contraction ('sign-restriction' FAVAR)

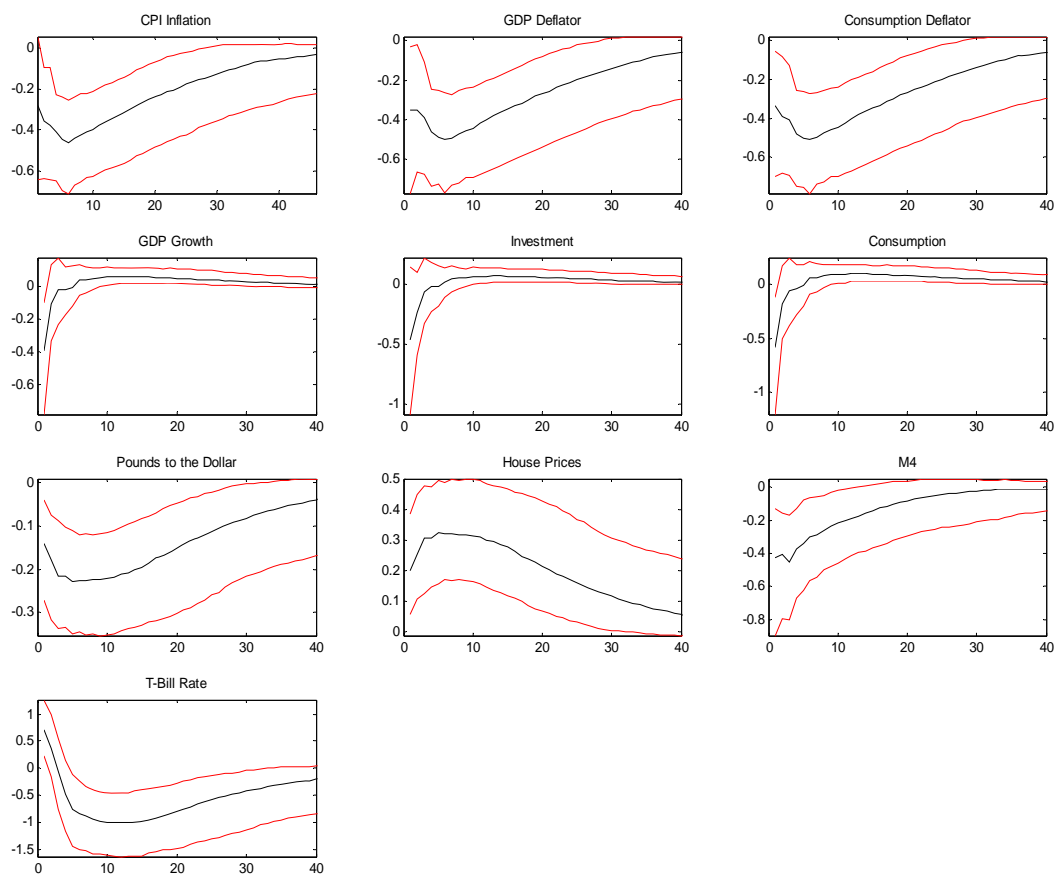


Chart 6: Impulse responses of key variables to a negative supply shock in ‘sign-restriction’ FAVAR

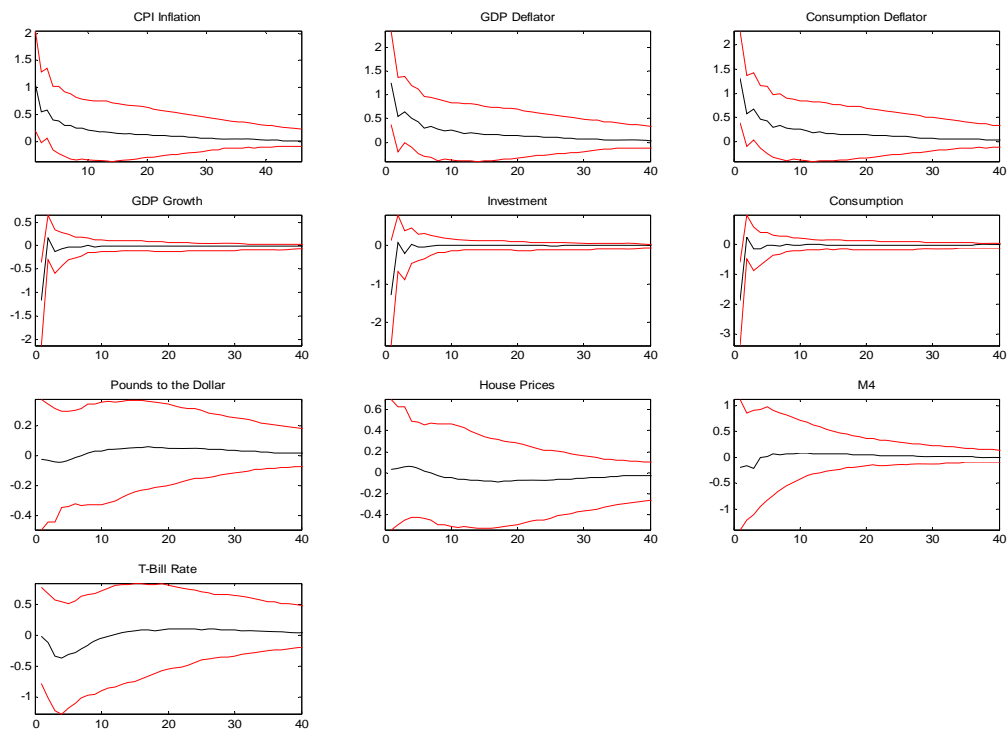


Chart 7: Impulse responses of key variables to a positive demand shock in ‘sign-restriction’ FAVAR

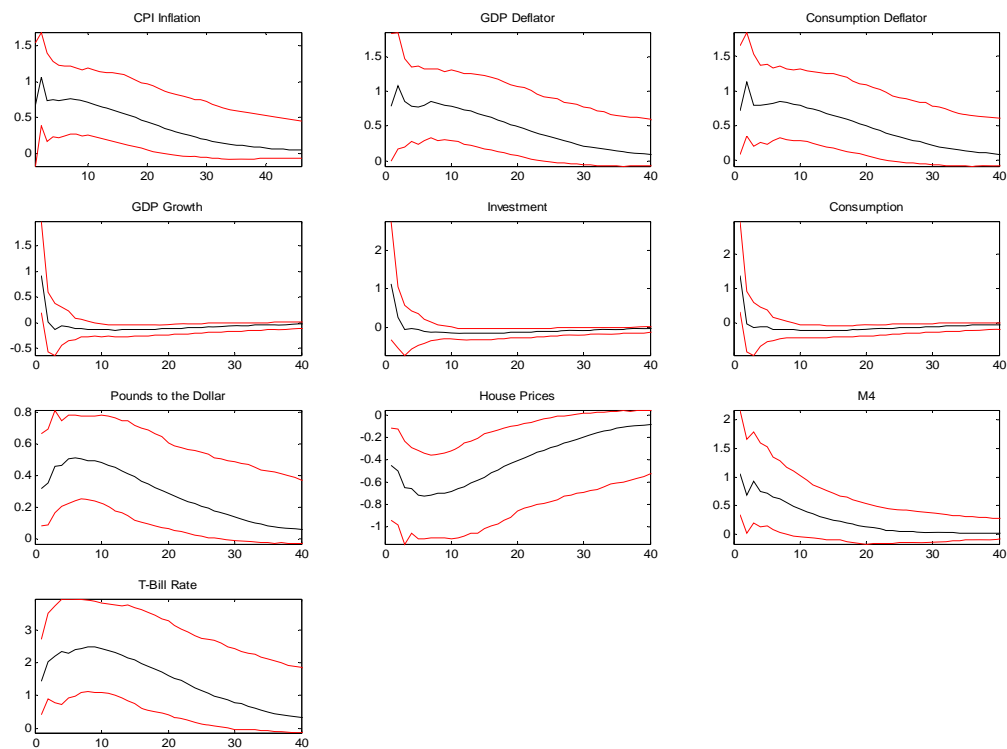


Chart 8: Impulse responses to a contractionary monetary policy shock in ‘Cholesky’ FAVAR with a structural break in 1993 Q1

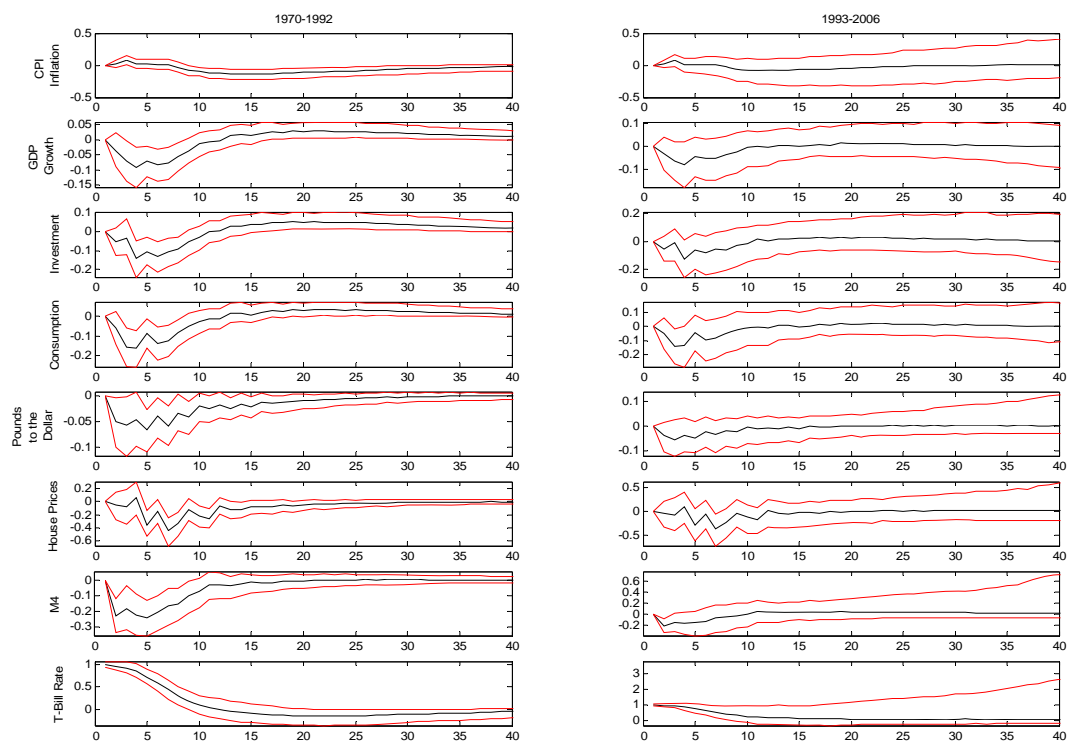


Chart 9: Impulse responses of disaggregated inflation rates and price levels to a monetary contraction (‘Cholesky’ FAVAR)

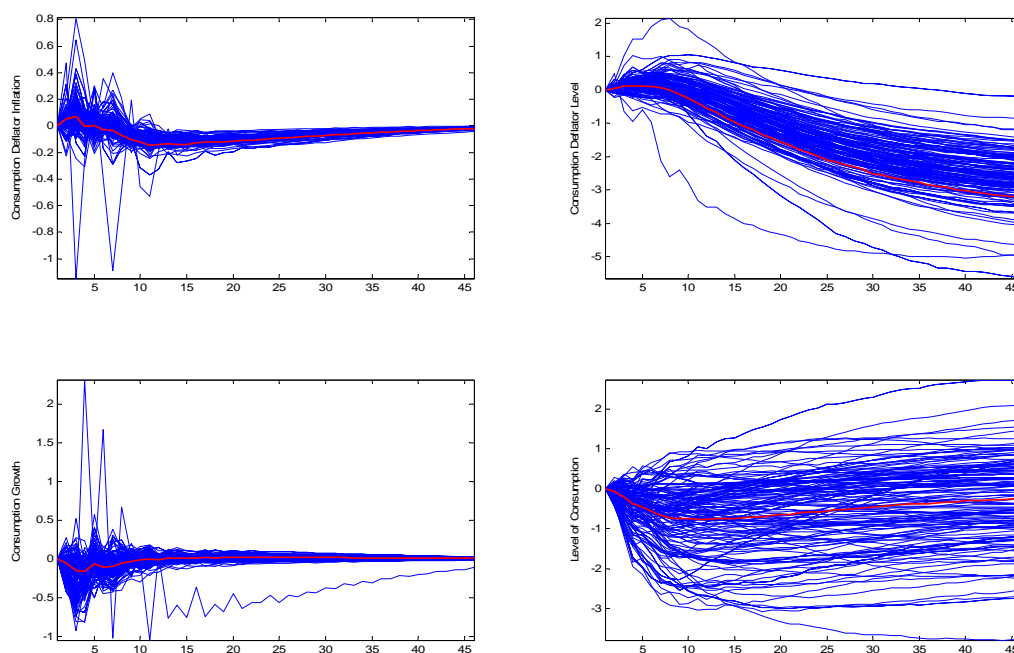


Chart 10: Response of disaggregated prices to a monetary contraction (Cholesky decomposition)

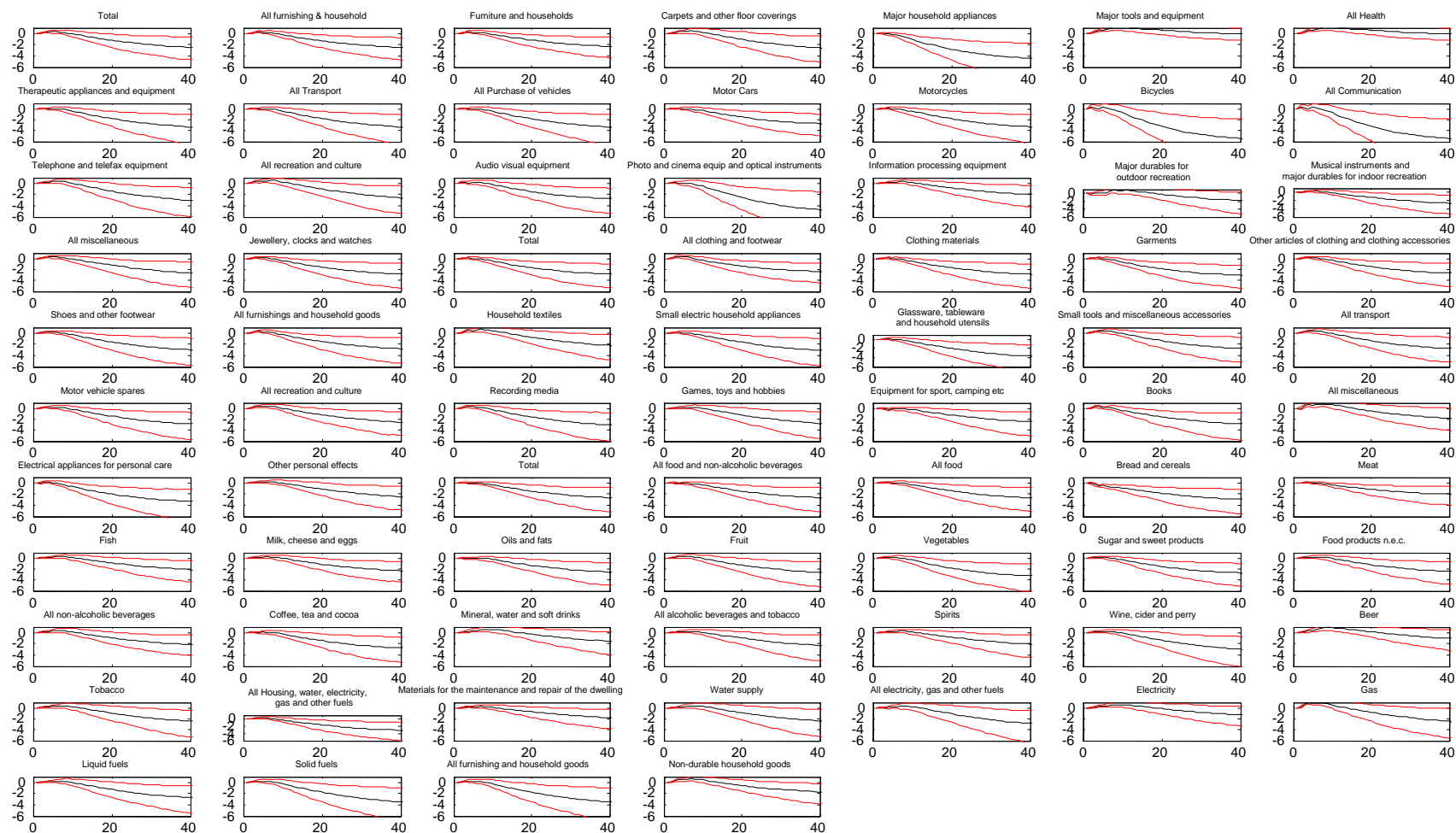


Chart 11: Response of disaggregated prices to a monetary contraction (Cholesky decomposition) continued

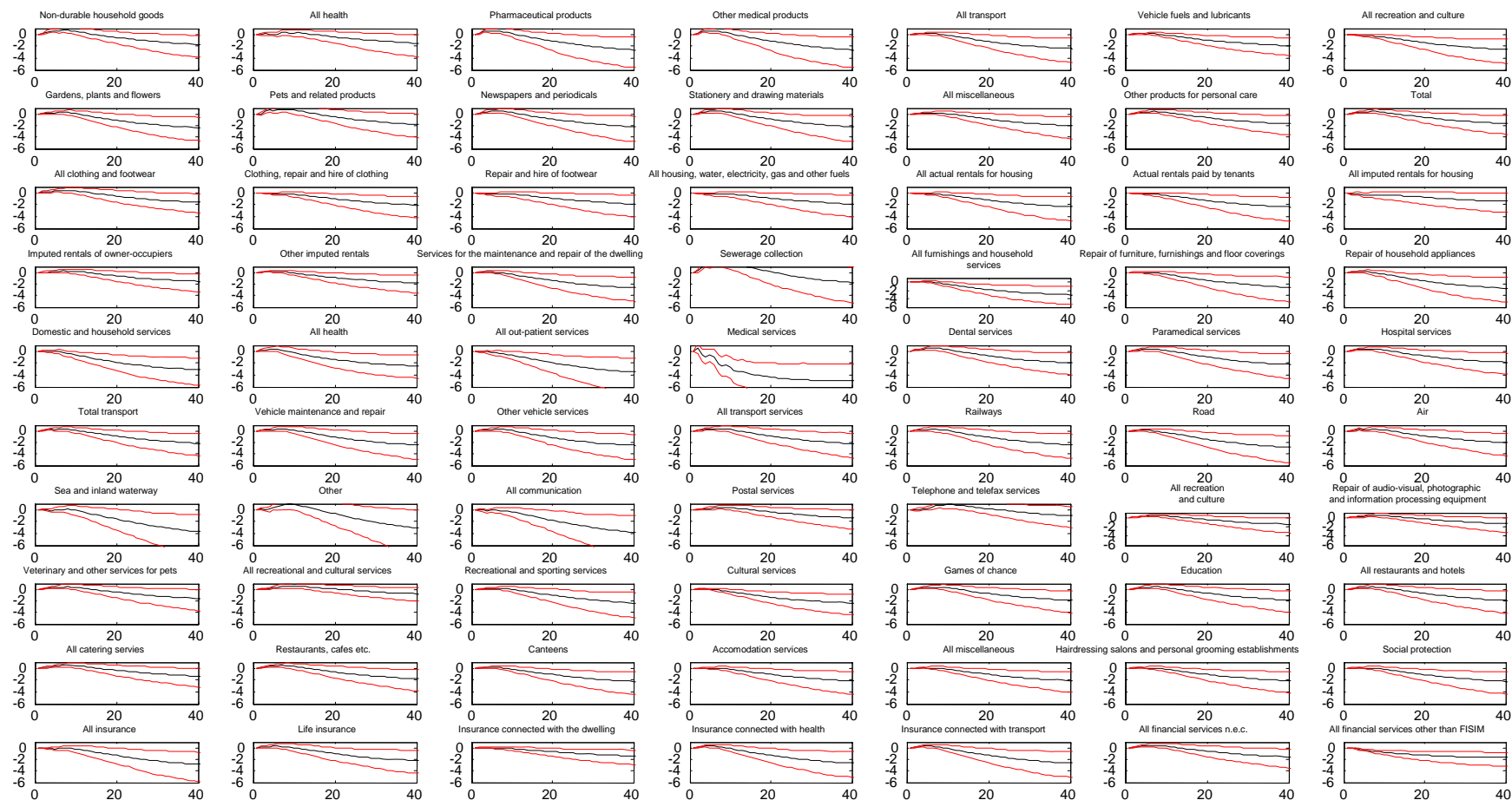


Chart 12: Impulse responses of disaggregated inflation rates and price levels to a monetary contraction ('sign-restriction' FAVAR)

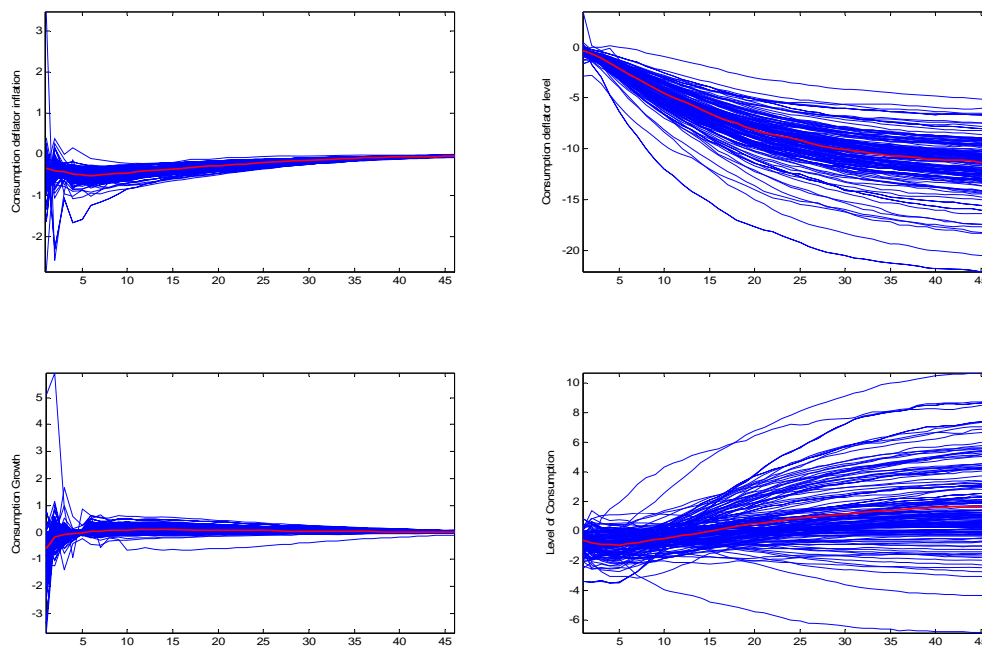


Chart 13: Response of disaggregated prices to a monetary policy shock (sign restrictions)

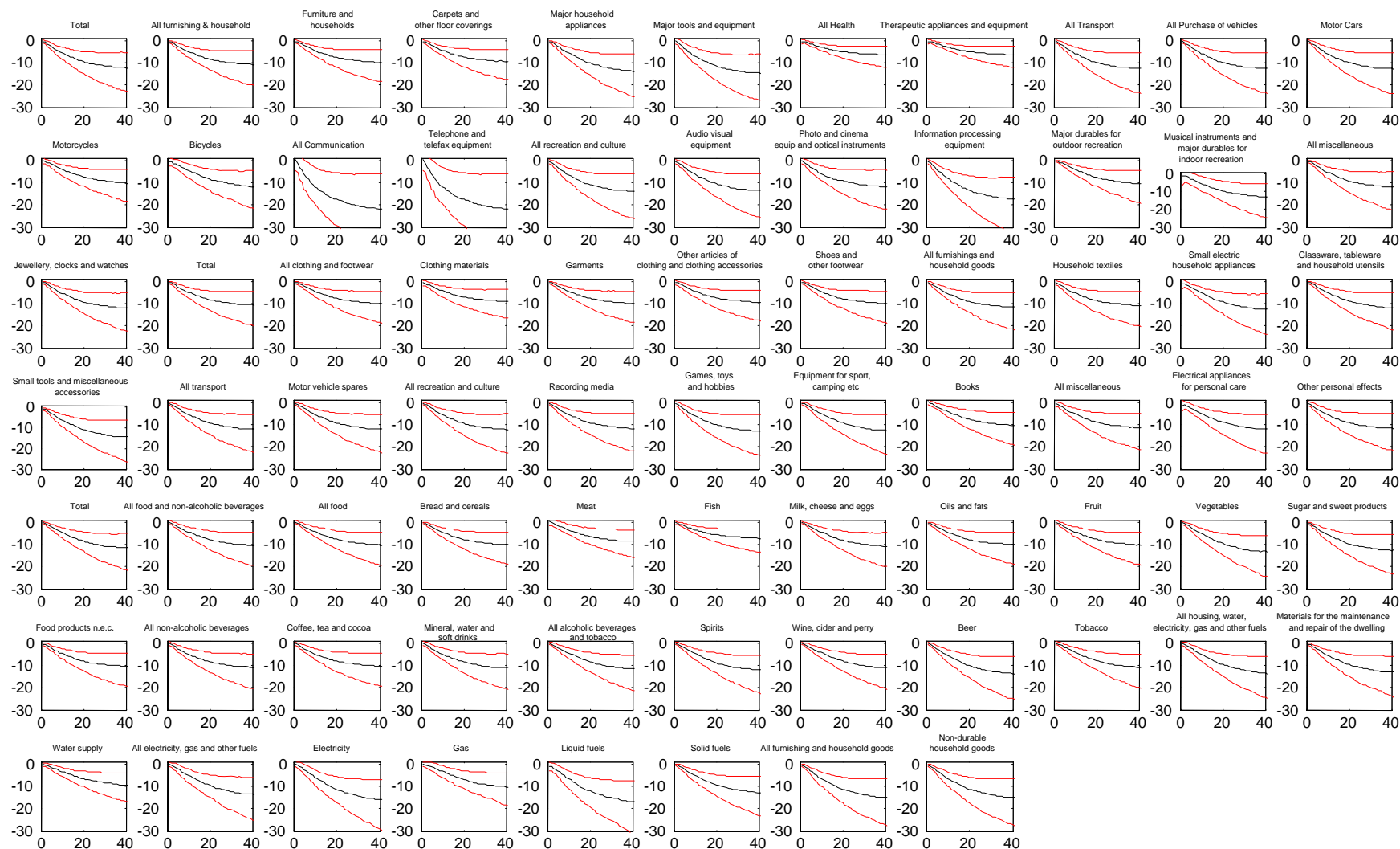


Chart 14: Response of disaggregated prices to a monetary policy shock (sign restrictions) continued

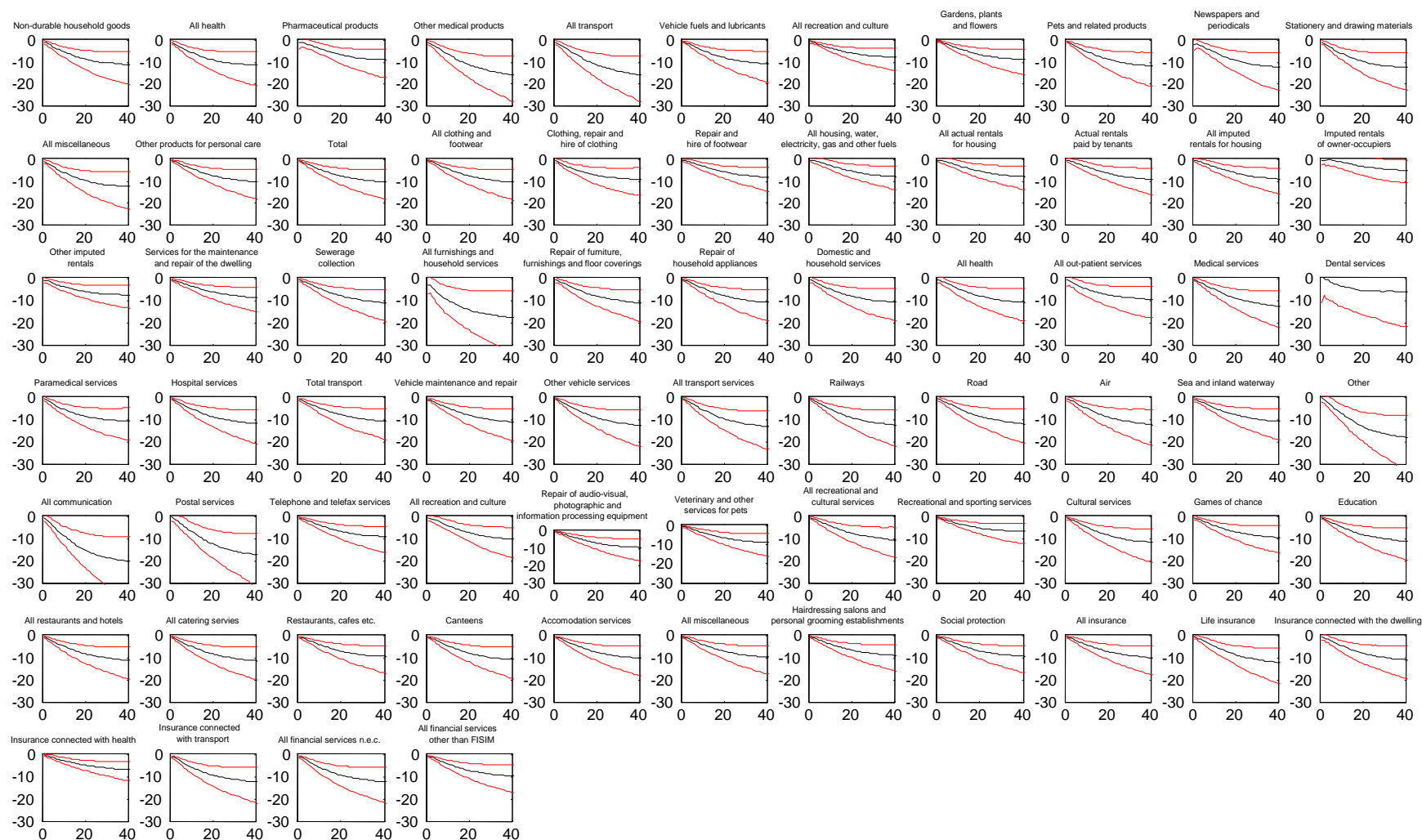


Chart 15: Proportion of sectoral monetary responses different from average inflation ('Cholesky' FAVAR)

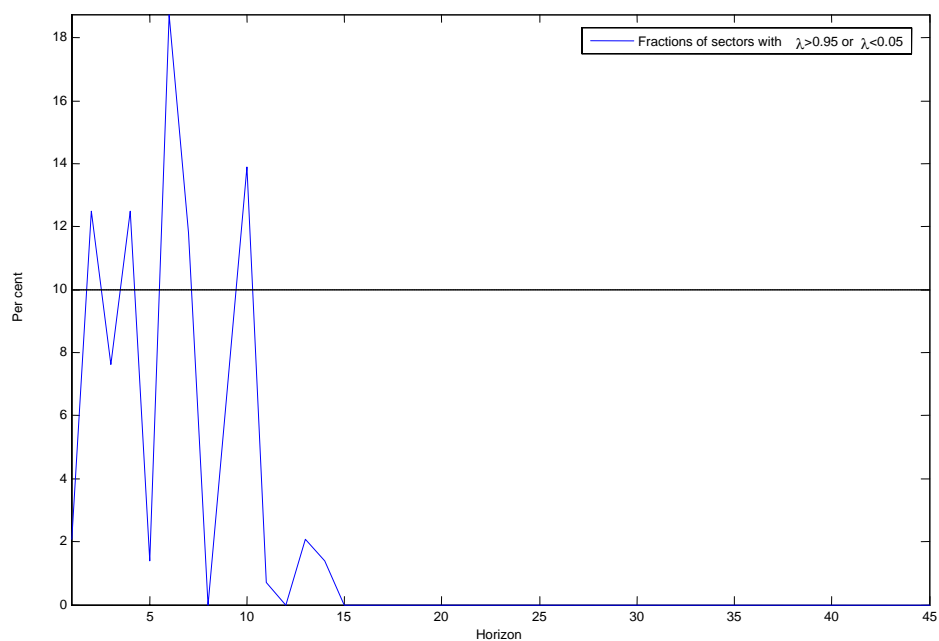


Chart 16: Proportion of sectoral monetary responses different from average inflation ('sign-restriction' FAVAR)

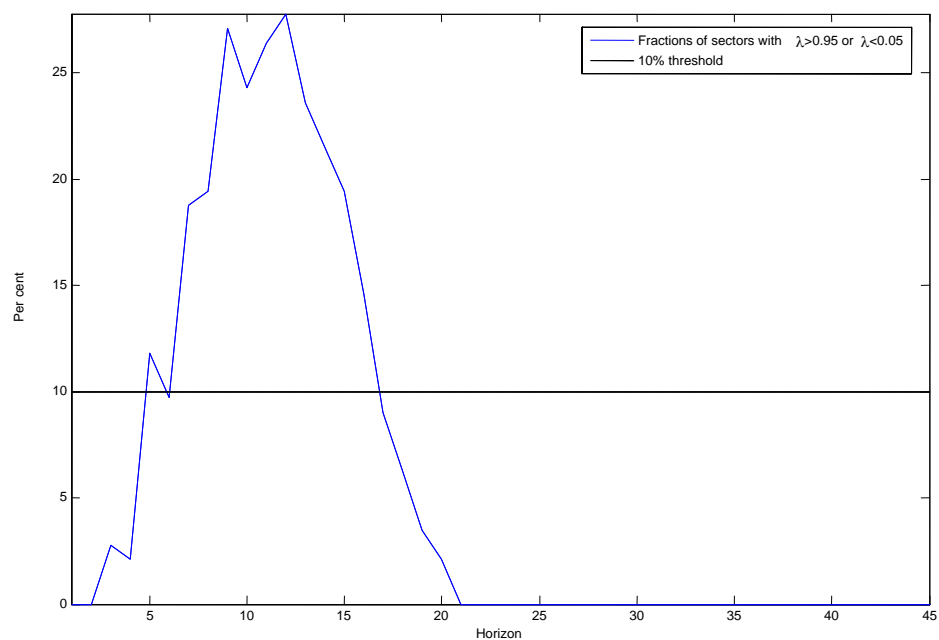


Chart 17: Disaggregated impulse responses to a contractionary supply shock ('sign-restriction' FAVAR)

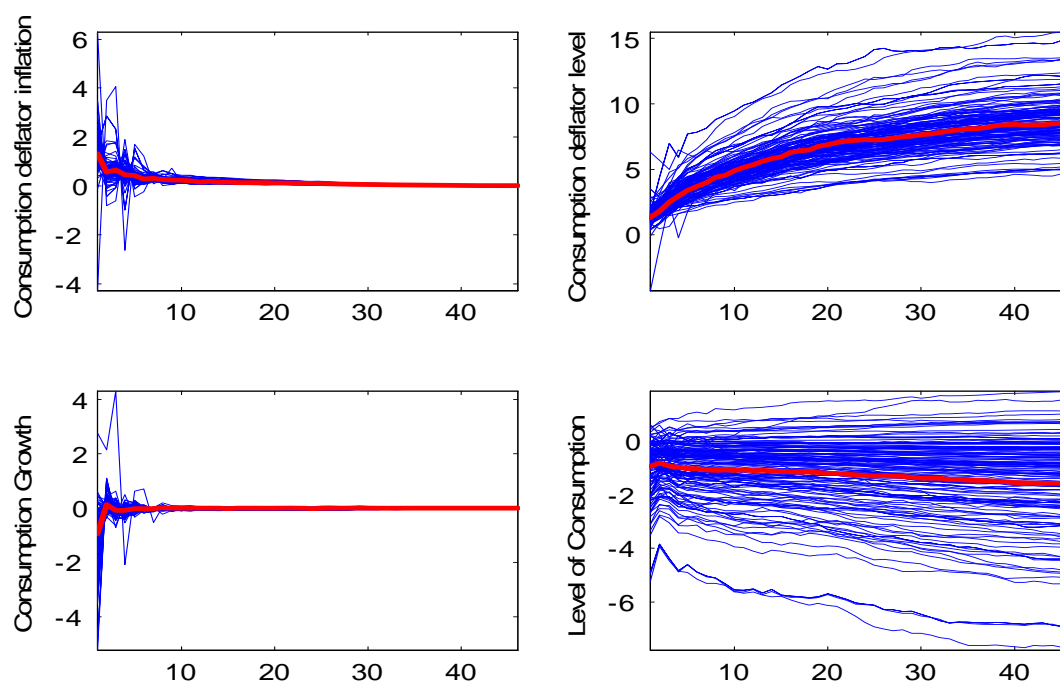


Chart 18: Disaggregated impulse responses to a positive demand shock ('sign-restriction' FAVAR)

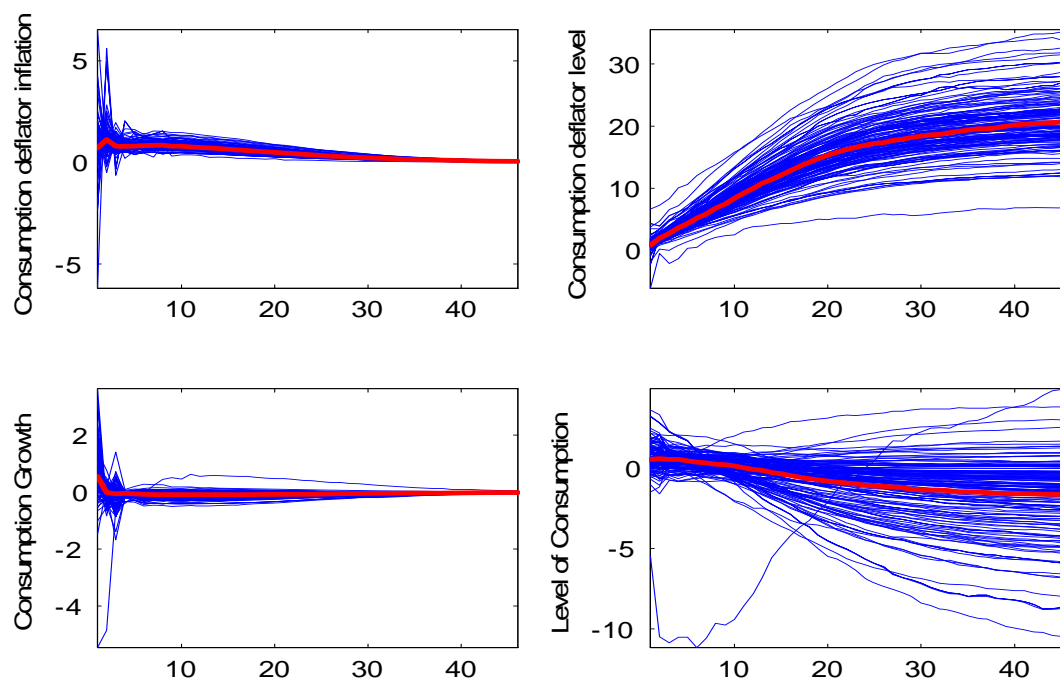


Table B: Volatility and persistence of inflation series ('Cholesky' FAVAR)

	Standard deviation of:		R ²	Persistence of:		
	Common component	Sector-specific component		Series	Common component	Sector-specific component
<u>Selected aggregate series</u>						
CPI	0.900	0.437	0.809	0.800	0.873	-0.006
GDP deflator	0.886	0.465	0.784	0.691	0.852	-0.201
RPI	0.866	0.500	0.750	0.629	0.810	-0.043
Consumption deflator (PC)	0.977	0.212	0.955	0.770	0.822	-0.081
Wages	0.756	0.654	0.572	0.637	0.866	0.097
<u>Disaggregate PC series</u>						
Unweighted average	0.692	0.690	0.501	0.229	0.473	-0.050
Median	0.723	0.690	0.523	0.304	0.549	-0.046
Minimum	0.263	0.307	0.069	-0.508	-0.398	-0.545
Maximum	0.952	0.965	0.906	0.703	0.854	0.609
Standard deviation	0.153	0.150	0.202	0.298	0.274	0.200

Table C: Volatility and persistence of inflation series ('sign-restriction' FAVAR)

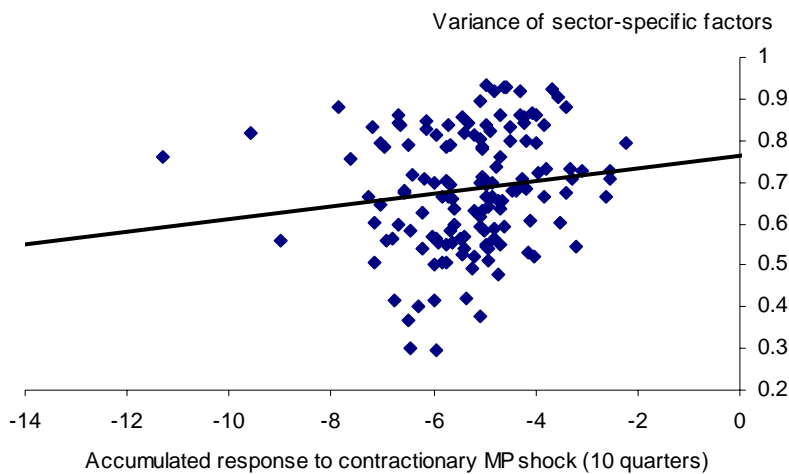
	Standard deviation of:		R ²	Persistence of:		
	Common component	Sector-specific component		Series	Common component	Sector-specific component
<u>Selected aggregate series</u>						
CPI	0.862	0.506	0.744	0.800	0.826	-0.209
GDP deflator	0.891	0.453	0.794	0.691	0.810	-0.232
RPI	0.883	0.469	0.780	0.629	0.835	-0.085
Consumption deflator (PC)	0.980	0.201	0.960	0.770	0.840	-0.069
Wages	0.650	0.760	0.423	0.637	0.826	0.197
<u>Disaggregate PC series</u>						
Unweighted average	0.683	0.698	0.491	0.229	0.500	-0.048
Median	0.708	0.706	0.502	0.304	0.582	-0.041
Minimum	0.215	0.306	0.046	-0.508	-0.421	-0.441
Maximum	0.952	0.977	0.907	0.703	0.845	0.529
Standard deviation	0.158	0.150	0.204	0.298	0.298	0.191

Table D: Correlations between sector-specific factors and monetary policy responses

	Accumulated impulse response		
	10 quarters	20 quarters	40 quarters
<i>Cholesky FAVAR</i>			
Variance of sector-specific factors	0.136	0.158*	0.158*
Persistence of sector-specific factors	0.110	0.189**	0.209**
<i>Sign-restriction FAVAR</i>			
Variance of sector-specific factors	0.183**	0.154*	0.136
Persistence of sector-specific factors	0.161*	0.166**	0.164**

* indicates significance at the 10% level

** indicates significance at the 5% level

Chart 19: Correlation between monetary policy response and the variance of sector-specific factors ('sign-restriction' FAVAR)**Table E: Correlations between sectoral characteristics and model-based results**

	Accumulated impulse responses			Sector-specific factors	
	10 quarters	20 quarters	40 quarters	Variance	Persistence
<i>Cholesky FAVAR</i>					
Gross profit share	0.228	0.307**	0.294**	-0.071	0.231*
Import intensity	-0.317**	-0.293**	-0.216	-0.151	-0.282**
Concentration ratio (5%)	0.165	0.121	0.073	0.312**	0.136
Concentration ratio (10%)	0.199	0.168	0.125	0.299**	0.158
<i>Sign-restriction FAVAR</i>					
Gross profit share	0.300**	0.213	0.177	-0.081	0.236*
Import intensity	-0.340**	-0.214	-0.189	-0.172	-0.256*
Concentration ratio (5%)	-0.126	-0.200	-0.240*	0.312**	0.070
Concentration ratio (10%)	-0.112	-0.193	-0.238	0.312**	0.080

* indicates significance at the 10% level

** indicates significance at the 5% level

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